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Factors affecting dentists' intention to adopt artificial intelligence: an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) model

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Abstract

Purpose – Advancements in science and technology have integrated artificial intelligence (AI) into dentistry, improving treatment processes, operational efficiency, and clinical outcomes. However, AI adoption among dentists remains underexplored, hindering progress in oral healthcare. This study aims to identify key barriers to AI adoption and examine factors influencing dentists' intention to use AI.

Design/methodology/approach – A quantitative cross-sectional approach was employed, utilizing self-administered questionnaires distributed online and across various dental clinics and hospitals in Ankara, Turkey. A total of 440 dentists participated in the study. Data analysis was conducted using SPSS and SmartPLS.

Findings – The study found that AI-anxiety negatively affects the intention to adopt AI in dentistry, showing a medium (almost large) effect that is stronger than other UTAUT factors such as performance expectancy, effort expectancy, and social influence, which demonstrated only small effects. Dentists with higher anxiety about learning and sociotechnical blindness are less likely to adopt AI, while concerns about job replacement and AI-configuration have less but still significant impact.

Research limitations/implications – These results contribute to the growing body of knowledge on technology adoption in oral healthcare and provide practical implications for technology developers, policymakers, and other stakeholders seeking to facilitate AI integration in dentistry.

Originality/value – This study provides novel insights into AI adoption in dentistry, offering guidance for future development and integration, and addressing a critical research gap in a growing field—particularly in Turkey, where implementation is still in its early stages.

Keywords Artificial intelligence, AI adoption, AI-anxiety, Digital dentistry, Oral healthcare digitalization, UTAUT

Paper type Research article

1. Introduction

Oral diseases pose a major global health and economic burden (ranking among the top four most costly conditions), causing pain, anxiety, disfigurement, and reduced self-confidence that impair daily functioning and quality of life (Hassani *et al.*, 2021; World Health Organization, 2023). Globally, 3.9 billion people are affected by oral diseases, with untreated tooth decay impacting 44% of the population—making it the most prevalent condition among the 291 listed diseases (World Health Organization, 2023). The same report notes that in 2020, oral cancer accounted for approximately 377,713 new cases and 177,757 deaths.

In Turkey, oral cancer caused 1,330 deaths in 2018—representing 0.33% of total mortality, with an age-adjusted death rate of 1.48 per 100,000 people—and by 2023, the country ranked 163rd globally in oral cancer-related deaths (World Life Expectancy, 2024). A recent study involving 11,091 participants found a high prevalence of dental caries (76.5%) among Turkish

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children and adults (Orhan *et al.*, 2024). As of 2022, Ankara's population of 5,782,285 was served by 4,872 practicing dentists, yielding a dentist-to-population ratio of 1:1,187 (Türk Dişhekimleri Birliği, 2023), posing challenges for addressing the oral disease burden and ensuring adequate access to care. Inequalities persist, particularly in rural areas where access to dental services is significantly lower than in urban centers (Ekici *et al.*, 2017; Orhan *et al.*, 2024). The World Health Organization's (2022) report on Turkey highlighted widespread dental caries, periodontal disease, and low oral hygiene awareness. It emphasized the urgent need for comprehensive oral health policies, better access to dental services—especially in rural areas—and an increase in dental professionals to reduce these disparities.

The integration of Artificial Intelligence (AI) into oral healthcare holds substantial potential for addressing many of these current challenges. AI, defined as machines and systems designed to perform tasks that typically require human intelligence (e.g. learning and problem-solving), is transforming many aspects of oral healthcare and dentistry (Pethani, 2021). AI operates by analyzing data through algorithmic systems to identify patterns, learn from experience, and make informed decisions without explicit programming (Schwendicke *et al.*, 2020). In dentistry, AI-enhanced diagnostic tools offer greater precision and early detection, particularly in identifying carious lesions and malignancies before they progress and require invasive, resource-intensive, and costly treatments (Schwendicke *et al.*, 2021). By improving diagnostic accuracy and reducing the need for late-stage interventions, AI technologies have demonstrated long-term cost-effectiveness, despite high initial implementation costs (Schwendicke *et al.*, 2021). These technologies can also enhance adherence to preventive care through AI-assisted communication, which fosters trust and engagement—especially among individuals with heightened health anxieties (Kosan *et al.*, 2022). Moreover, AI can alleviate practitioners' workload by automating routine diagnostics, aiding treatment planning, and supporting less experienced clinicians in decision-making (Ducret *et al.*, 2022), thereby improving efficiency and care quality without the need for workforce expansion. AI also offers a means to reduce disparities in dental care access through remote diagnostics, mobile AI-powered screening tools, and tele-dentistry platforms, particularly benefiting underserved populations (Khoury *et al.*, 2024). Additionally, AI can help improve awareness of poor oral care by enhancing patients' ability to visually identify issues like caries on radiographs, thereby increasing their belief in the diagnosis, acceptance of treatment, and active involvement in their care (Kosan *et al.*, 2022). At the policy level, AI-supported surveillance systems enable real-time monitoring of oral health trends, treatment outcomes, and population needs—facilitating evidence-based decision-making, targeted interventions, and effective resource allocation (AlQaifi *et al.*, 2024; Ducret *et al.*, 2022).

While AI holds transformative potential for improving healthcare outcomes, its uneven adoption is often influenced by systemic factors such as infrastructure readiness, digital literacy, and resource availability (Samuel-Okon and Abejide, 2024). Financial constraints in many publicly or government-funded dental facilities also hinder the adoption of advanced technologies like AI, potentially widening the digital divide between public and private sectors and influencing intentions to adopt such innovations (Modha, 2023). Integrating AI into dentistry presents several specific challenges, including high initial costs, limited access to AI technologies, and a shortage of expert knowledge among dental professionals (Aboalshamat, 2022; Baby *et al.*, 2023; Schwendicke *et al.*, 2021). The absence of AI-specific training contributes to significant knowledge gaps, making it difficult for practitioners to integrate AI into routine clinical practice (Aboalshamat, 2022; Pethani, 2021). Furthermore, AI lacks essential human qualities such as empathy and intuition, raising ethical concerns regarding its role in clinical decision-making (Shan *et al.*, 2021). Privacy issues, data governance, regulatory uncertainty, and skepticism about AI potentially replacing human judgment further complicate adoption (Pethani, 2021; Roganović *et al.*, 2023). Overcoming these barriers requires targeted support—such as training, infrastructure investment, and funding—as well as enhanced digital literacy, clear regulatory policies, and continuous human oversight to promote the responsible integration of AI into dentistry (Baby *et al.*, 2023; Grischke *et al.*, 2020; Samuel-Okon and Abejide, 2024; Shan *et al.*, 2021). Additionally, advancing AI solutions in oral healthcare demands transparent, ethical, and environmentally sustainable implementation to ensure equitable and lasting progress (Ducret *et al.*, 2022). Ensuring inclusivity, fairness, and transparency in AI system design is essential to avoid exacerbating existing health disparities and to build trust in these tools across diverse populations (Khoury *et al.*, 2024).

Another major challenge for AI adoption in oral care is that, despite strong interest within the dental field, its actual use remains limited (Aboalshamat, 2022). For example, by 2024, only 18% of dental professionals in the U.S. and 35% of dentists in the UK had integrated AI into their practices (Healthful Helps, 2024). Additionally, while 85% of Saudi dental professionals recognize AI's value in preventive dentistry, many lack the necessary knowledge and skills for full integration (Abouzeid *et al.*, 2021). Although awareness of AI technologies is gradually increasing, actual usage remains low due to concerns like job displacement. For instance, 70.3% of Pakistani dentists are familiar with applications such as computer-aided design and manufacturing (CAD-CAM) and digital records, despite viewing AI as a supportive tool (Sajjad *et al.*, 2021). Confidence in the practical application of AI also remains limited, with some practitioners fearing that AI could fundamentally disrupt the profession's structure (Hamd *et al.*, 2023). Moreover, AI adoption in clinical practice continues to be constrained primarily because of psychological and practical concerns such as fears of job displacement, AI-related anxiety, and uncertainty about its clinical relevance and effectiveness (Aboalshamat, 2022; Schwendicke *et al.*, 2020). Notably, this anxiety has been found to be relatively prominent among Turkish dentists (Bulut *et al.*, 2024). However, whether such anxiety actually influences their intention to adopt AI in clinical practice remains underexplored, highlighting the need for further research to understand how these concerns shape adoption decisions.

This study aimed to fill this gap by first identifying key barriers to AI adoption and then applying the Unified Theory of Acceptance and Use of Technology (UTAUT), focusing on core constructs (performance expectancy, effort expectancy, and social influence) as predictors of behavioral intention. Additionally, the model was extended to include AI anxiety and to deepen understanding of its multidimensional nature by examining its subdimensions (learning, job replacement, sociotechnical blindness, and AI-configuration anxieties). Focusing on the Turkish context, the findings offer a more comprehensive understanding of the psychological and structural factors influencing AI adoption in dentistry. These insights can support policymakers, healthcare administrators, and technology developers in creating targeted strategies that address dental professionals' specific concerns, ultimately facilitating AI integration and improving the quality and efficiency of oral healthcare delivery.

2. Theoretical background and hypothesis

2.1 UTAUT

Venkatesh *et al.* (2003) introduced the UTAUT, combining insights from eight prominent models, including the Technology Acceptance Model, the Theory of Reasoned Action, the Theory of Planned Behavior, and others. UTAUT was created to provide a more comprehensive and unified view of technology acceptance, addressing gaps and inconsistencies found in prior models, making it a valuable framework for predicting technology adoption and usage. The model's key constructs include performance expectancy, effort expectancy, and social influence, which serve as independent variables, while behavioral intention is the dependent variable. Performance expectancy refers to the degree to which users believe that using a technology will improve their job performance, while effort expectancy refers to how easy users think it will be to use a new technology. Social influence refers to the degree to which users perceive that those who are important to them (colleagues, managers, mentors etc.) believe they should use the technology. According to this model, performance expectancy may drive dentists to adopt AI if they believe it will enhance their performance or clinical outcomes, while effort expectancy and social influence can impact adoption if dentists perceive AI as easy to use and observe important figures to them using or endorsing AI.

In addition to the theoretical support from Venkatesh *et al.* (2003), empirical evidence also supports that performance expectancy, effort expectancy, and social influence affect intention. This is evident in healthcare-related AI adoption research (Cheng *et al.*, 2022; Dingel *et al.*, 2024; Huang *et al.*, 2024; Kim *et al.*, 2024; Ratta *et al.*, 2025) as well as in other contexts such as electronic health system implementation (Abdelrahman *et al.*, 2025), educational technology acceptance (Gogus *et al.*, 2012), and AI adoption in human resource recruitment (Tanantong and Wongras, 2024). Thus, the following hypotheses are proposed:

H1. Performance expectancy positively affects intention.

H2. Effort expectancy positively affects intention.

H3. Social influence positively affects intention.

2.2 AI-anxiety

AI-anxiety is defined as the fear or unease individuals experience due to the rapid integration of AI technologies into society and concerns about its potential future impact (Kim *et al.*, 2025). AI-anxiety arises from concerns about job displacement, privacy violations, loss of human control over AI systems, and the spread of AI-generated misinformation and biases (Kim *et al.*, 2025). Unlike fear, which is a singular, short-term emotion, AI-anxiety is a multidimensional, long-term experience influenced by multiple factors. These factors differ from those linked to earlier technological anxieties, mainly because AI is capable of autonomous thinking and decision-making (Kim *et al.*, 2024; Terzi, 2020). Wang and Wang (2022) were among the first to recognize this complexity, identifying four key dimensions of AI-anxiety: learning anxiety (discomfort with being left behind and difficulty in understanding AI), job replacement anxiety (the fear that AI could replace dentists' roles and diminish their professional significance), sociotechnical blindness (concerns about AI's societal and ethical implications, such as misuse or malfunction), and AI-configuration anxiety (unease toward humanoid or complex AI technologies that may be perceived as intimidating or threatening).

Technology-related anxiety hinders technology adoption, with lower anxiety levels correlating with higher acceptance (Abdelrahman *et al.*, 2025; Gogus *et al.*, 2012). Neudert *et al.* (2020) found that public perceptions of AI are polarized, with many viewing it as harmful and feeling anxious about its risks, particularly regarding job loss—even among professionals such as doctors and lawyers. AI-anxiety significantly influences public attitudes toward AI and robotics, where perceived usefulness increases acceptance, while perceived threats, particularly concerns about job displacement, heighten anxiety and reduce adoption (Vu and Lim, 2022).

In healthcare, AI-anxiety negatively impacts the intention to adopt AI-based healthcare technologies and contributes to negative attitudes toward such technologies, further hindering their adoption (Dingel *et al.*, 2024; Kwak *et al.*, 2022a). Higher AI literacy and positive attitudes are associated with lower AI-anxiety (Sarman and Tuncay, 2024). Reducing AI-related apprehension can enhance individuals' intention to use AI, as lower AI learning anxiety correlates with more favorable attitudes toward AI (Kim *et al.*, 2025). AI-anxiety significantly impacts behavioral intentions by linking personal fears to future actions; higher anxiety levels can restrict engagement with AI, while lower levels may promote acceptance (Wang and Wang, 2022). Additionally, individuals who perceive AI as a threat to their work and employment experience higher levels of AI-anxiety, reinforcing the idea that negative perceptions of AI increase anxiety and reduce adoption (Yigit and Acikgoz, 2024).

In dentistry, AI-anxiety arises from challenges such as high costs, limited training, job displacement fears, ethical concerns, and AI's inability to replicate human empathy (Hamd *et al.*, 2023; Schwendicke *et al.*, 2021; Pethani, 2021). Many dentists experience anxiety about AI and its limitations, further complicating its adoption (Hamd *et al.*, 2023; Bulut *et al.*, 2024).

Hence, it is hypothesized that:

H4. AI-anxiety negatively influence intention.

The research model (Figure 1) depicts the hypothesized relationships where dentists' AI adoption intention is influenced by UTAUT constructs (performance expectancy, effort expectancy, and social influence) and by AI-anxiety as a second-order construct comprising four dimensions (learning, sociotechnical blindness, job replacement, and AI-configuration).

3. Methodology

3.1 Measurements

To achieve the objective of this research, a four-part questionnaire was used. The first section collected demographic information as discussed earlier. The second section assessed perceived barriers using eight items adapted from Aboalshamat (2022), with binary "Yes" or "No" responses. The scale was translated from English to Turkish following the translation and cultural adaptation guidelines of Lee *et al.* (2019). This process involved expert review by four lecturers from Atılım University and was followed by a pilot test with 15 postgraduate students to ensure face and content validity. No further modifications were required. The third section measured UTAUT constructs using the Turkish-validated scale by Gogus *et al.* (2012), originally developed by Venkatesh *et al.* (2003). This scale includes four items each for performance expectancy, effort expectancy, and social influence, and three for behavioral intention, all rated on a 5-point Likert scale. In this study, AI-anxiety was conceptualized as a second-order construct to reflect multiple distinct yet interrelated dimensions that collectively represent broader psychological, multisource resistance toward AI. Accordingly, the fourth section assessed AI-anxiety using Terzi's (2020) Turkish adaptation of Wang and Wang's scale, which was employed because it comprehensively captures the multiple sources of anxiety through four subcategories: learning anxiety (8 items), job replacement anxiety (6 items), sociotechnical blindness (4 items), and AI-configuration anxiety (3 items), all measured on a 7-point Likert-type scale. This higher-order modeling approach has also been employed in recent AI-adoption research (Yigit and Acikgoz, 2024).

3.2 Data collection and analysis

This study employs a quantitative research approach with a convenience sampling technique, collecting data through self-administered questionnaires distributed via various online platforms, dental clinics, and hospitals using Google Forms and QR codes. The Atilim University Ethics Board approved the study. Participants were required to be licensed dentists actively practicing and residing in Ankara. In 2022, Turkey had approximately 46,378 dentists,

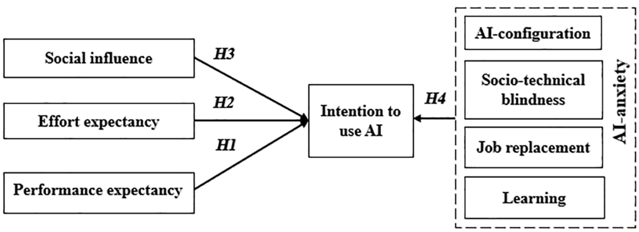

Figure 1. Study's model. Source: Authors' own creation

with 4,872 working in universities, public hospitals, and private practices in Ankara (Türk Dişhekimleri Birliği, 2023). Based on this population, a 5% margin of error, and a 95% confidence level, the required sample size was calculated to be approximately 357. To account for potential analysis issues, 440 responses were collected (Hair *et al.*, 2019). Data analysis was conducted using SPSS and SmartPLS.

Partial least square structural equation modeling (PLS-SEM) was chosen for data analysis due to its strong predictive capability, particularly for complex research models like the one in this study, as well as its flexibility regarding data distribution and statistical assumptions (Sarstedt *et al.*, 2019). This method accommodates both reflective and formative models, maximizing the explained variance in endogenous constructs (Hair *et al.*, 2019). Following Anderson and Gerbing's (1988) recommendation, a two-step analysis approach was adopted (Sarstedt *et al.*, 2019). In the first step, the reflective measurement model was evaluated based on indicator reliability, convergent validity, and discriminant validity, while the formative measurement model was assessed for collinearity, and the significance and relevance of factor weights. In the second step, the structural model's explanatory and predictive power was tested by considering the path coefficient (β), *p*-values, determination coefficient (R^2), effect sizes (f^2), and predictive relevance (Q^2) to evaluate the model's robustness (Hair *et al.*, 2019).

Since this research employed a cross-sectional design—collecting dependent and independent variables simultaneously from the same sources—there was a risk of common method bias (CMB), which can inflate or deflate observed relationships between variables (Kock *et al.*, 2021). To mitigate this risk, procedural remedies were implemented, including psychological separation of measures, varied Likert scales, and counterbalanced question order. To assess potential bias, Harman's single-factor test revealed that four factors accounted for 34.69% of the variance—well below the 50% threshold. A full collinearity test also found all variance inflation factor (VIF) values to be below 3.3 (Kock *et al.*, 2021), indicating that CMB is not a significant concern and that the observed relationships are likely valid.

4. Findings

4.1 Respondents' profile

Table 1 shows that among the 440 dentists surveyed, 56% were male, and 52.3% were aged between 24 and 44 years. The majority held a bachelor's degree (53.3%) and worked in private practice (62.3%). Over half (50.5%) had 11–20 years of experience, and 76.4% were general dentists. While 48% reported being knowledgeable about AI, social media was the primary source of information for 79.3% of respondents. A strong majority (87.5%) expressed interest in taking AI courses in the future. However, only 22.4% were currently using AI in their practice, and among them, just 84 respondents (19.1% of the total sample) provided examples of AI applications. The most common uses were in diagnosis, treatment planning, and research (33.3% each), while other applications—such as smile design, lecture preparation, and managerial tasks—were mentioned by 2% or fewer.

4.2 Barriers to use AI

Table 2 presents the barriers to AI adoption in dentistry, with the most significant challenges being the lack of AI courses in dentistry (78.2%), the time required to learn AI (77.5%), and the perceived need for a coding background (70%).

4.3 Assessment of measurement model (first order)

The first-order measurement model was assessed reflectively by evaluating all eight constructs for internal consistency and reliability. Table 3 presents the loadings, composite reliability (CR), Cronbach's alpha (CA), and average variance extracted (AVE) (Hair *et al.*, 2019). Most indicator loadings exceeded the 0.70 threshold, except for one item in the AI-Configuration construct: "I find humanoid AI techniques/products (e.g. humanoid robots) scary." Removing

Table 1. Demographic details

Demographics	Category	Frequency (%) (N = 440)
Gender	Female	194 (44.0%)
	Male	246 (56.0%)
Age	24–44	230 (52.3%)
	45–56	210 (47.7%)
Education level	Bachelor	234 (53.3%)
	Master	151 (34.6%)
	Doctorate	55 (12.2%)
Workplace	Private practice	274 (62.3%)
	Health ministry	85 (19.3%)
	University	81 (18.4%)
Experience years	Less than 5 years	125 (28.4%)
	5–10 years	47 (10.7%)
	11–20 years	222 (50.5%)
	More than 20 years	46 (10.5%)
Specialty	General dentist	336 (76.4%)
	Orthodontist	26 (5.9%)
	Endodontist	10 (2.3%)
	Periodontics	9 (2.0%)
	Prosthetics	19 (4.3%)
	Pedodontics	11 (2.5%)
	Others	29 (6.6%)
Understanding of AI	No idea	15 (3.4%)
	Only what I get from various media platforms	134 (30.5%)
	Familiar but not confident to apply it in my work	89 (20.2%)
	Understand AI concept	202 (45.9%)
Sources of AI Information	From social media	349 (79.3%)
	College, conferences, education	159 (36.1%)
	Family or friends	46 (10.5%)
	TV	36 (8.2%)
	Newspapers or magazines	73 (16.6%)
	No source	11 (2.5%)
Interest in AI course	Yes	385 (87.5%)
	No	55 (12.5%)
Current use of AI in practice	Yes	98 (22.4%)
	No	342 (77.6%)

Source(s): Authors' own creation

Table 2. Barriers to use AI

Perceived barriers to AI use	Yes (%)	No (%)
No courses on AI in dentistry	344 (78.2%)	96 (21.8%)
Too much time to learn AI	341 (77.5%)	99 (22.5%)
Requires coding background	308 (70.0%)	132 (30.0%)
AI is difficult to learn	258 (58.6%)	182 (41.4%)
AI is not relevant to dental work	174 (39.5%)	266 (60.5%)
Not interested in AI in dentistry	132 (30.0%)	308 (70.0%)
AI violates patient privacy	93 (21.1%)	347 (78.9%)
Lack of interest in AI	90 (20.5%)	350 (79.5%)

Source(s): Authors' own creation

Table 3. First-order measurement model assessment

Construct	Items	Loadings	CA	CR	AVE
Performance expectancy	PE_1	0.728	0.759	0.847	0.581
	PE_2	0.752			
	PE_3	0.751			
	PE_4	0.816			
Effort expectancy	EE_1	0.762	0.764	0.850	0.586
	EE_2	0.741			
	EE_3	0.794			
	EE_4	0.763			
Social influence	SI_1	0.793	0.771	0.853	0.593
	SI_2	0.796			
	SI_3	0.763			
	SI_4	0.726			
Learning	L_1	0.754	0.907	0.924	0.575
	L_2	0.750			
	L_3	0.790			
	L_4	0.750			
	L_5	0.728			
	L_6	0.729			
	L_7	0.763			
	L_8	0.792			
Job replacement	JR_1	0.764	0.870	0.906	0.659
	JR_2	0.771			
	JR_3	0.841			
	JR_4	0.825			
	JR_5	0.822			
	JR_6	0.797			
Sociotechnical blindness	STB_1	0.823	0.864	0.907	0.710
	STB_2	0.861			
	STB_3	0.867			
	STB_4	0.818			
AI-configuration	AC_1	0.505	0.852	0.910	0.772
	AC_2	0.867			
	AC_3	0.873			
Intention	BI_1	0.849	0.775	0.869	0.689
	BI_2	0.811			
	BI_3	0.830			

Source(s): Authors' own creation

this item significantly improved the construct's reliability and validity—CA increased from 0.625 to 0.802, CR from 0.804 to 0.910, and AVE from 0.590 to 0.834. For all remaining constructs, CR and CA values exceeded the recommended 0.70 threshold, and AVE values were above 0.50, confirming both internal consistency and convergent validity (Hair *et al.*, 2019).

Discriminant validity was verified using the Heterotrait-Monotrait Ratio (HTMT) in Table 4, with all values below 0.85 (Henseler *et al.*, 2015), Overall, the results confirm that the model meets the required standards for reliability and validity, making it suitable for further analysis.

4.4 Assessment of measurement model (second order)

AI-Anxiety was conceptualized as a higher-order formative construct encompassing four subdimensions: AI-configuration, job replacement, learning, and sociotechnical blindness. It was assessed using the disjoint two-stage approach (Sarstedt *et al.*, 2019). In the first stage,

Table 4. HTMT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) AI-configuration								
(2) Intention	0.620							
(3) Effort expectancy	0.422	0.762						
(4) Job replacement	0.493	0.565	0.386					
(5) Learning	0.359	0.650	0.567	0.340				
(6) Performance expectancy	0.482	0.792	0.853	0.426	0.577			
(7) Social influence	0.476	0.794	0.754	0.390	0.841	0.814		
(8) Sociotechnical blindness	0.450	0.683	0.492	0.466	0.343	0.499	0.428	

Source(s): Authors' own creation

latent variable scores were generated using the PLS-algorithm and saved for use in the second stage, where bootstrapping with 5,000 subsamples was employed to assess the formative construct. Results in Table 5 and Figure 2 show that all factor weights and loadings were statistically significant ($p < 0.05$), supporting the inclusion of these subdimensions in the model. This confirms the validity and reliability of the measurement model, allowing for further analysis. Among the subdimensions, learning and sociotechnical blindness contributed more strongly to AI-anxiety than job replacement and AI-configuration.

Table 5. Second-order measurement model assessment

Constructs	Factors	VIF	Weights	*t*-values	*p*-values	Loadings	*t*-values	*p*-values
Anxiety	AI-configuration	2.847	0.277	5.397	0.000	0.667	16.020	0.000
	Job replacement	2.510	0.210	3.915	0.000	0.642	14.173	0.000
	Learning	3.199	0.489	9.383	0.000	0.762	20.119	0.000
	Sociotechnical blindness	3.126	0.413	7.767	0.000	0.744	18.627	0.000

Source(s): Authors' own creation

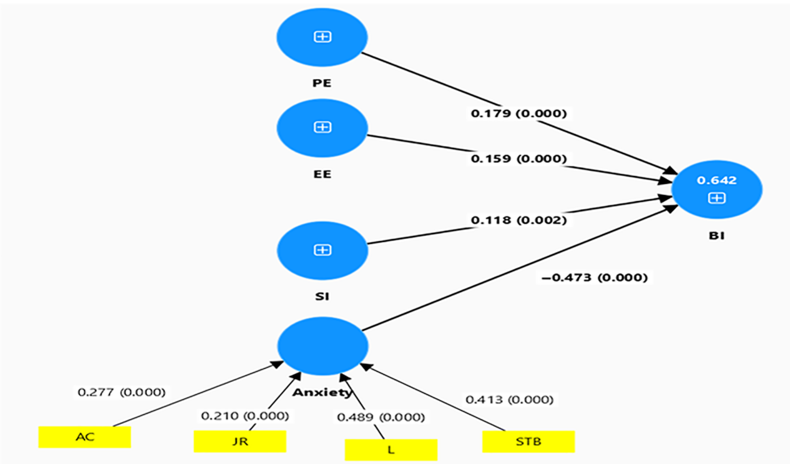

Figure 2. Structural model assessment. Source: Authors' own creation

4.5 Assessment of the structural model

Table 6 and Figure 2 present the path coefficients, *p*-values, and corresponding *t*-values computed using PLS bootstrapping to assess the structural model (Hair *et al.*, 2019). In Figure 2, blue circles represent the latent constructs along with their β coefficients and *p*-values (in brackets), while yellow boxes depict the subdimensions of AI-anxiety—learning (L), sociotechnical blindness (STB), AI configuration (AC), and job replacement (JR)—with their respective weight estimates and *p*-values (in brackets).

All hypotheses (H1–H3) related to UTAUT were supported ($p < 0.05$), with performance expectancy [$\beta = 0.179$, $t = 4.147$], effort expectancy [$\beta = 0.159$, $t = 3.602$], and social influence [$\beta = 0.118$, $t = 2.892$], positively influencing intention, all exhibiting small effects [$f^2 = 0.040$, 0.035, 0.017], respectively. H4 is also supported ($p < 0.05$), indicating that AI-anxiety negatively influenced intention [$\beta = -0.473$, $t = 12.047$], with a medium (almost large) effect [$f^2 = 0.311$].

The explanatory power of the model was assessed using R^2 values (Table 6), which represent the proportion of variance in the dependent variables explained by the independent variables (Hair *et al.*, 2019). The R^2 value indicates that 64.2% of the variance in intention is explained by the independent variables, demonstrating acceptable explanatory power of the model.

4.5.1 PLSpredict. The PLSpredict algorithm with 10-fold cross-validation and 10 repetitions confirmed the model's strong predictive power. All items had positive Q^2predict values, indicating predictive relevance, and the RMSE (root mean square error) was lower for the PLS-SEM model compared to the LM (linear models), demonstrating the model's strong predictive capability (Shmueli *et al.*, 2019). The cross-validated predictive ability test results further supported the model's validity, with PLS loss values for intention significantly lower than the indicator average loss ($p < 0.05$), confirming predictive validity. Additionally, PLS loss values for intention and the overall model were significantly lower than those of the linear model, reinforcing the model's predictive strength, thus confirming its strong predictive validity (Sharma *et al.*, 2022).

5. Discussion

First, this research identified prominent key barriers hindering AI adoption in dentistry. Consistent with Aboalshamat (2022), most participants reported significant obstacles such as the absence of AI courses in dental education, the perception that learning AI is time-consuming, the belief that a coding background is required, and the notion that AI is difficult to learn. However, whereas Aboalshamat's study highlighted a lack of general interest in AI as a major barrier, this study found it to be less significant—possibly reflecting the growing recognition of AI's value and potential among dental professionals. Additionally, concerns about privacy violations, lack of interest in AI in dentistry, and the perception that AI is irrelevant to dental work were considered less significant barriers in both studies.

Second, this study found that both performance expectancy and effort expectancy (H1–H2) had significant effects on dentists' intention to use AI. These findings align with previous research on general IT acceptance (Venkatesh *et al.*, 2003), educational technology (Gogus *et al.*, 2012), electronic health system implementation (Abdelrahman *et al.*, 2025), and AI adoption in healthcare (Ratta *et al.*, 2025; Cheng *et al.*, 2022; Huang *et al.*, 2024; Kim *et al.*, 2024; Dingel *et al.*, 2024). In most of these studies, performance expectancy was the strongest predictor of intention, with effort expectancy playing a secondary but meaningful role. However, in the present study, both constructs—along with social influence (H3)—showed similarly small effects on intention. The effect of social influence aligns with the UTAUT framework and some AI-adoption studies (Dingel *et al.*, 2024; Huang *et al.*, 2024; Kim *et al.*, 2024), in contrast to others that reported it as insignificant (Cheng *et al.*, 2022; Gogus *et al.*, 2012; Kwak *et al.*, 2022a; Ratta *et al.*, 2025; Tanantong and Wongras, 2024). These results indicate that dentists are more willing to adopt AI when they perceive clear clinical benefits,

Table 6. Structural model assessment

Hypothesis	Relationships	VIF	β	p-values	t-values	f^2		R^2	Decision
H1	Performance expectancy → Intention	2.034	0.179	0.000	4.147	0.040	>Intention	0.642	Supported
H2	Effort expectancy → Intention	2.242	0.159	0.000	3.602	0.035			Supported
H3	Social influence → Intention	2.263	0.118	0.002	2.892	0.017			Supported
H4	Anxiety → Intention	2.013	−0.473	0.000	12.047	0.311			Supported

Source(s): Authors' own creation

such as improved diagnostic accuracy and workflow efficiency. Their intention is also shaped by the perceived ease of use and encouragement from trusted peers or institutional leaders, which builds confidence in adopting unfamiliar or evolving technologies and underscores the importance of professional endorsement. The small effect sizes for the UTAUT constructs on intention in this study may stem from limited hands-on experience and low familiarity with AI, both of which are crucial for shaping positive attitudes and strengthening intention (Kwak *et al.*, 2022b). Without consistent exposure, users may struggle to perceive AI as useful or easy to use, reducing confidence and dampening the influence of these UTAUT constructs (Kwak *et al.*, 2022a). Additionally, the insufficient integration of AI into educational curricula can weaken usability perceptions and lessen the impact of both effort expectancy and social influence (Yigit and Acikgoz, 2024).

The PLS-SEM output confirmed that H4 concerning AI-anxiety was supported, revealing that AI-anxiety negatively influenced dentists' intention to adopt AI, with a medium effect size. This finding aligns with earlier research demonstrating that technological anxiety can hinder adoption intentions (Gogus *et al.*, 2012; Abdelrahman *et al.*, 2025). It also supports recent studies in the healthcare AI-adoption literature, where AI-anxiety is increasingly recognized as a psychological barrier to intention (Dingel *et al.*, 2024; Ratta *et al.*, 2025; Yigit and Acikgoz, 2024). Similarly, Kwak *et al*. (2022a, 2022b) demonstrated that anxiety reduces AI adoption intentions among nursing students by decreasing positive attitudes and increasing negative ones. These studies link anxiety to concerns about AI's accuracy, transparency, ethical implications, and its potential to diminish professional autonomy—all of which heighten perceived risk and resistance to AI adoption. Anxiety impedes adoption by undermining users' confidence and willingness to engage with new technologies. This often stems from low self-efficacy, limited prior exposure, and fear of failure, particularly in complex or high-risk clinical environments. This study's results also show anxiety's moderate negative effect on intention, contrasting with the small positive effects of performance expectancy, effort expectancy, and social influence This difference can be explained by the fact that, unlike rational evaluations of usefulness, ease of use, or peer influence, anxiety is rooted in fear, uncertainty, and perceived risk. It reflects deeper emotional and psychological barriers that can override logical considerations—especially in unfamiliar or high-stakes clinical contexts—positioning anxiety as a stronger predictor of intention.

The current analysis also revealed that learning anxiety and sociotechnical blindness exert the strongest influence on AI-anxiety among dentists, while concerns about AI configuration and job replacement have comparatively weaker effects. These discrepancies may be explained by studies suggesting that the opacity and unpredictability of AI systems intensify sociotechnical concerns and complicate learning, making them more pressing than abstract or long-term worries such as job security (Cheng *et al.*, 2022; Dingel *et al.*, 2024; Ratta *et al.*, 2025). In contrast to this research findings, Yigit and Acikgoz (2024) found that nursing students with high AI-anxiety were most affected by sociotechnical blindness, followed by concerns about job replacement and learning, with AI configuration being the least influential. Despite these variations, sociotechnical blindness emerged as a significant concern across both groups, reflecting shared fears that AI may undermine empathy, ethical sensitivity, and the human aspects of care Significant learning anxiety in both samples might stem from the technical complexity of clinical AI tools, which heightens uncertainty and emphasizes perceived skill gaps. This concern is more pronounced among dentists, who perform high-precision procedures and may feel greater pressure to master new technologies. In contrast, job replacement anxiety appeared more significant among nursing students, likely due to a stronger sense of occupational vulnerability. Dentists, may perceive their roles as more secure, given the manual and procedural nature of their work, which is less susceptible to future automation. In both groups, AI configuration anxiety was found to be a less influential factor, suggesting that fears related to interacting with or operating AI tools are relatively minor barriers to adoption.

6. Theoretical and practical implications

Theoretically, this study contributes to the literature on AI adoption in dentistry and expands empirical knowledge in Türkiye, where research on this topic remains limited. By applying and extending the UTAUT model to include AI-anxiety, the study offers a more comprehensive framework that incorporates psychological barriers alongside traditional predictors such as performance expectancy, effort expectancy, and social influence. While AI-anxiety is increasingly recognized as a barrier to AI adoption in healthcare (Dingel *et al.*, 2024; Ratta *et al.*, 2025; Yigit and Acikgoz, 2024), but its role in dentistry remains underexplored. This study contributes to filling that gap by examining AI-anxiety specifically among dentists. Moreover, recognizing that AI-anxiety is multidimensional and distinct from earlier forms of technological anxiety—due to AI's ability to make decisions and learn autonomously—the study provides a nuanced understanding of its dimensions (learning, job replacement, sociotechnical blindness, and AI configuration anxieties) and how they contribute to overall AI-anxiety, subsequently shaping adoption intentions.

From a practical perspective, this study offers valuable guidance for policymakers, healthcare administrators, technology developers, and other stakeholders in designing more effective, tailored strategies to enhance AI adoption among dentists, potentially transforming the industry. By identifying key barriers and examining various factors that affect the intention to adopt AI, the study helps stakeholders recognize and address obstacles to adoption. These insights provide a foundation for targeted educational, managerial, and policy-level interventions, and the study proposes multidimensional strategies and actionable recommendations to support the smoother integration of AI technologies into dental practices.

Since AI-anxiety significantly reduces dentists' intention to use AI, it must be addressed through targeted, evidence-based strategies tailored to specific sources of concern. To reduce learning anxiety, modular training programs should introduce foundational concepts step-by-step before progressing to more complex topics. Virtual simulations or controlled practice environments can also provide psychologically safe spaces that encourage exploration, build confidence, and promote comfortable engagement with AI tools. Educational institutions play a vital role in preparing future practitioners for AI integration; however, limited AI content in current dental curricula and a lack of professional training opportunities exacerbate the knowledge gap (Hamd *et al.*, 2023). Educational institutions can overcome these barriers by offering specialized courses, workshops, and training programs on AI applications in dentistry, thereby preparing future dentists to confidently use these technologies. By bridging the gap between theoretical knowledge and practical implementation, these initiatives ensure that dental professionals acquire the necessary skills to integrate AI into their practices. Embedding digital literacy into curricula through hands-on workshops, applied training, and simulation-based exercises, reinforced by real-world applications, will empower dentists to use AI more confidently and competently (Grischke *et al.*, 2020; Schwendicke *et al.*, 2020). In addition, educational materials should be practical rather than overly technical to foster trust in AI technology. Developers can further support adoption by offering guided onboarding, simplified workflows, intuitive interfaces, and minimizing technical jargon to enhance usability, reduce anxiety and perceived effort, and improve expectations about ease of use.

To manage sociotechnical anxiety, training programs should include content on data ethics, algorithmic bias, and transparency to foster informed trust in AI systems. Engaging dentists in the design and feedback processes might help ensure these technologies align with healthcare values and practical realities. Prioritizing ethical principles such as fairness, equity, and impartiality in AI design can facilitate broader acceptance among dental professionals. Creating channels for continuous user feedback will allow systems to evolve alongside shifting workplace expectations and professional norms. Currently, regulatory bodies are working to establish frameworks for AI use in dentistry to provide guidelines that ensure safety, effectiveness, and reliability. However, clearer legal regulations are still needed, especially regarding accountability in cases of algorithmic bias. To address concerns about AI's role and impact on patient care, establishing ethical guidelines and regulatory standards is critically important. Dental institutions should implement transparent governance and ethical codes related to AI use to help dentists adopt these technologies more safely. It must also be emphasized that AI systems should operate under constant human supervision and be recognized as professional support tools.

In terms of job replacement anxiety, AI must be clearly framed as a supportive tool rather than a replacement for clinical expertise. Involving dentists in the implementation planning process gives them a sense of agency and helps them understand how AI can support—not diminish—their professional growth. This involvement might also reinforce positive attitudes toward AI's impact on performance expectancy, which can be further encouraged by integrating case studies, clinical trials, and pilot programs into professional development to demonstrate how AI improves clinical decision-making and patients' outcomes.

Finally, to reduce AI configuration anxiety, systems must be designed to be accessible and supportive. Real-time assistance through help desks, user forums, or chatbots should be available, and in-app guidance must offer timely, contextual support. Developers should consider existing infrastructure and provide clear pathways for integration or necessary upgrades, helping dentists navigate implementation with greater confidence. Interfaces that allow for easy reversal or adjustment of actions can further reduce the fear of making irreversible mistakes, making the adoption process more approachable and less intimidating.

This study revealed that, although its effect is small, social influence is an important factor shaping dentists' intentions to use AI. This suggests that interactions within professional networks and among peers play a key role in accelerating AI adoption. Senior dentists and respected researchers who advocate for and endorse AI can motivate their younger colleagues. Therefore, organizing forums, workshops, seminars, and similar scientific gatherings that encourage experience and knowledge sharing within the dental community is essential. These interactive platforms facilitate peer learning, making the transition to AI more widespread and secure. As a result, dentists will be better equipped to use these technologies confidently and gain the necessary knowledge and support to integrate AI into their practices.

7. Conclusion

This research had two objectives: the first was to identify key barriers to AI adoption in dentistry, and the second was to examine the factors affecting dentists' intention to adopt AI. The study identified major barriers to AI adoption in dentistry, with the most prominent being limited AI education, the perception that learning AI is time-consuming, and the belief that coding skills are required. It also found that performance expectancy, effort expectancy, and social influence positively influence dentists' intentions to use AI, although with small effect. In contrast, AI-anxiety emerged as the strongest negative predictor, showing a medium-to-large effect. Among AI-anxiety subdimensions, learning anxiety and sociotechnical blindness were the most significant contributors, while concerns related to AI-configuration and job replacement were less influential but still statistically significant. Despite certain limitations, this study fills a gap in the literature and provides theoretical, empirical and practical insights for various stakeholders aiming to promote broader AI adoption in the oral health community.

8. Future research and limitations

One limitation of this research is the use of self-administered questionnaires, which might have introduced social desirability bias. To mitigate this, Google Forms was used and anonymity was ensured to provide greater privacy and reduce social pressure. Another limitation is the study's focus on Ankara. Future research should expand the geographical scope to other cities in Turkey and internationally (e.g. Europe or the Americas) to enhance generalizability, explore cross-cultural differences, and allow meaningful comparisons that may reveal contextual variations in attitudes toward AI. The cross-sectional design also limits the ability to capture changes over time, so longitudinal studies could offer insights into how AI adoption behaviors and attitudes evolve. Future research should also examine whether these findings apply to other healthcare fields beyond dentistry. Given that most participants were willing to learn about AI despite moderate anxiety and low current usage, future studies could include post-intervention or post-training assessments and in-depth case studies to explore how increased knowledge influences long-term adoption and anxiety reduction. Evaluating structured educational programs would also provide valuable insights for developing effective AI training and promoting broader adoption across healthcare. Finally, research should examine structural and societal factors such as organizational digital readiness and access to AI technologies in oral healthcare institutions, especially in under-resourced areas, as they may pose additional challenges.

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