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Original Research

Perceptions and Acceptance of Artificial Intelligence in Dentistry: A Comprehensive Examination of Dentists' Attitudes and Behavioural Intentions Towards AI Integration in Clinical Setting

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Abstract

Background: The integration of Artificial Intelligence (AI) in dental care presents numerous benefits. However, fostering a proactive attitude is essential to ensure that these advancements lead to positive developments within dental practices. This study primarily focuses on examining the acceptance of AI technologies among dental professionals.

Objective: The present study aims to explore the perceptions and acceptance of dentists towards the integration of AI in dentistry through Technology Acceptance Model (TAM) as a theoretical framework.

Methods: By adopting descriptive research design, the study involved systematic collection of primary data from dental professionals to gain insights into their perceptions, attitudes, and acceptance of AI technologies in their professional environment. Using judgmental sampling, the researcher selected participants with first-hand experience relevant to the study's topic. Consequently, a sample of 200 dental professionals who are actively using or planning to use AI technologies have been considered as prospective respondents.

Results: The findings of the study reveal that dental professionals are aware about the usage of AI in dentistry and AI implementation is most notable in Orthodontics at 34%, followed by a significant use in Endodontics and Prosthodontics at 18.5% and 17.5% respectively. The results based on Structural Equation Modelling (SEM) indicate that the variable "perceived ease of use" positively influences dental professionals' attitudes towards its use in dentistry. Furthermore, the positive attitude has significantly influenced their behavioural intention to use, which in turn positively affected the actual usage of AI in dental practices.

Conclusion: Though the overall impact of AI in dentistry is largely positive, it is notable that perceived usefulness did not significantly influence dentists' attitudes. This discrepancy indicates that the majority of dentists are aware of the benefits of integrating AI in dentistry, conflicting with expectations, the variable perceived usefulness did not have a significant impact on the attitudes of dental professionals towards AI.

Keywords: artificial intelligence; dentistry; diagnostics; technology acceptance model (TAM)

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Background

Artificial intelligence (AI) is a subdomain in computer science focused on developing systems capable of performing tasks requiring human intelligence (Sarker, 2022). AI is a technological advancement that is rapidly progressing all over the world across the sector (Pavaloaia & Necula, 2023).Though artificial intelligence emerged in the 1950s, due to several limitations, such as restricted analysis, limited data, and storage issues, it did not see much success. Its first use in the medical field could be traced to 1970, with the Internist-1 tool that helped in experimental diagnosis used in internal medicine (Miller et al., 1982). In 2000, artificial intelligence started making its way into healthcare too (Kaul et al.,2020). Gradually, artificial intelligence expanded its reach into specific fields of dental care in diagnosis, planning the treatment, and managing patients. Dentistry, like other medical fields, is also witnessing a paradigm shift with artificial intelligence interventions for offering a wide range of dental care services. (Mahesh Batra & Reche, 2023).

AI has revolutionized dental care profoundly through deep learning and machine learning, providing an opportunity for personalized services with advanced diagnosis and planning patients' treatment more efficiently. AI integration ranges from simple diagnosis to advanced dental services such as neck and head oncology, restorative dentistry, orthodontics, radiology, and periodontics, providing delta services more efficiently (Ahmed et al., 2021). But the integration of AI in dentistry comes with several challenges, such as restricted data availability, apprehensive attitude of dentists to use AI in routine practice, privacy and security of data, and ethical issues of using patients' data for diagnosis all of which need to be addressed (Schwendicke et al., 2020). However, the impact of AI integration in dentistry expands to enhancing the patients' experience by optimizing and personalizing the services by syncing the data right from scheduling, real-time communication, billing and reducing overall waiting time (Bohr & Memarzadeh, 2020). The advanced diagnosis creates 3D modelling and simulations for better decision making for dentists by creating virtual images of patients' dental issues like Virtual Surgical Planning (VSP) that offers advanced 3D models for jaw realignment procedures (Shan et al., 2021).

Additionally, AI driven chatbots and virtual assistants provide constant access to information and post-treatment guidance (Wang et al., 2023). Convolutional and artificial neural networks and genetic algorithms are also possible through AI integration in dentistry based on machine learning and deep learning algorithms (Babu et al., 2021). Inspite of dental radiology being the most frequent AI technique used for dental diagnosis, advanced techniques based on deep learning, especially designed for image analysis through Convolutional Neural Networks (CNNs) that diagnose peripheral radiographs of dental problem detection (Lee et al., 2018). Apart from image analysis, CNN algorithm also supports dentists in classifying 'Periodontits' that is most common dental issues found among patients (Kim et al., 2020). AI integration in dentistry also detects oral cancer, lymph nodes and other orofacial diseases easily (Bas et al., 2012; Hwang et al.,2019). AI integration in dentistry provides several benefits to dental healthcare. Not only does it enhance the diagnosis but also helps in managing treatment, thereby reducing the manpower requirement and the overall cost. With the countless benefits of AI integration, it is essential for a country like India to adopt it completely in dental healthcare to deal with the growing number of diseases, limited healthcare staff, and poor infrastructure. Understanding dentists' perspective is the most critical factor that should be studied in order to assess the adoption of AI in dentistry and bring it into mainstream. Hence, to connect the AI integration in dentistry to dentists, it is essential to study the attitude of clinical practitioners towards AI adoption. Therefore, this study focuses on dentists' perception and attitudes towards AI adoption into their dental practice. Based on Technology acceptance model (TAM) framework developed by (Davis, 1987), this study seeks to identify the determinants of AI adoption among dentists.

Methods

Study design

The research adopts descriptive research design to evaluate dental professionals' perception of AI technologies when working in their professional environment. The chosen research design allows researchers to retrieve dental professionals' data systematically while investigating their reactions to AI technologies in their workplace. The subject's real-life experiences serve as the basis of this study so a descriptive research design becomes the most appropriate fit. Further, due to absence of any experimental involvement or interventions, descriptive research design is the most suitable approach for achieving the research objectives. To uphold ethical research standards, the questionnaire included a clear statement on informed consent. As the study involved human participants, respondents were provided with a detailed information about the study's objectives and privacy assurances prior to the survey. Written consent was obtained from participants, as they have agreed to the consent statement in the questionnaire before proceeding with the survey

Sample

Dental professionals from South Indian metropolitan areas became the study participants since they experience higher exposure to artificial intelligence tools in dental practice than practitioners located in smaller cities and rural areas. The researcher relied on judgmental sampling to select professional participants who possess relevant hands-on knowledge about the research subject. Since AI implementation in dental practice exists at a nascent stage, judgemental sampling approach ensures that the study gathers insights from professionals who have practical knowledge of these technologies, rather than including individuals with minimal or no relevant experience. This approach is crucial for understanding the attitudes, perceptions, and acceptance of AI technologies in dentistry. Informed consent from all respondents, ensuring they were aware of the study's purpose and voluntary nature

Setting

A sample of 200 dental professionals (50 professionals from each city) actively involved in using or planning to use AI technologies has been considered as prospective respondents. The cities included for the study are Chennai, Bangalore, Kochi and Hyderabad each known for their vibrant healthcare sectors and advancements in dental technology.

Instrument

To collect primary data, a structured questionnaire based on the Technology Acceptance model (TAM) was developed to conduct a survey. The questionnaire comprised important components of TAM such as External Variables, Perceived Usefulness, Perceived Ease of Use, Attitude Towards Using, Behavioural Intention to Use and Actual System Use. The "External Variable" section captured demographic variables like Gender, Age, Education, Specialization, Years of Experience. The other four components consisted questions that are designed based on Likert scale to assess participants' perceptions, attitudes, and intentions regarding AI adoption in dental practice. The participants of the survey were recruited through professional networks and dental associations. Email invitations to participate in the survey were sent accompanied by a brief description of the study's objectives.

Data analysis

Descriptive analysis and hypothesis testing for the study has been performed using hypothesis IBM SPSS. Further, Confirmatory factor analysis (CFA) was conducted to ensure construct validity, followed by path analysis to examine the causal relationships between TAM components using IBM SPSS AMOS. Structural Equation Modelling(SEM) is particularly used as it helps in validation measurement models and testing theoretical relationships between constructs such as Perceived Usefulness, Perceived Ease of Use, Attitude Towards Using, Behavioural Intention to Use, and Actual System.

Limitations

As the study focuses on metropolitan cities, the findings may not fully represent dental professionals in rural areas and semi urban areas, where access to advanced dental technologies and AI integration may be more limited due to the factors like infrastructural facilities, digital literacy and other technological constraints. This may limit the generality of the findings. Hence, future research should include a wide geographic region to better understand AI adoption across diverse settings.

Results

Demographic profile and specialization

The demographic profile in Table 1. reveals a balanced gender distribution among 200 respondents, with 50% male and 50% female, ensuring minimal gender bias and broad applicability of findings. Age distribution shows a predominance of younger to middle-aged adults, with 50% aged between 26-35 years and 46% within the 36-45 age bracket, suggesting greater engagement with the study's topic among these groups, while the older age group (45-54 years) represents only 4%, possibly reflecting sampling biases or varying interest levels. Educational background analysis indicates a significant representation of Master's and Doctorate degree holders, who make up 83% and 15% respectively. In terms of specialization, General Dentistry and Periodontics are the most represented at 29% and 22.5% respectively, indicating their prevalence in the professional community. The experience levels primarily include newer professionals, with 36% having 7 to 10 years of experience and 25.5% with 4 to 7 years, suggesting an appeal of the study's modern methods to those early in their careers. Lastly, AI implementation is most notable in Orthodontics at 34% and significant use in Endodontics and Prosthodontics at 18.5% and 17.5% respectively.

Table 1. Demographic Profile and Specialization, n=200

Age	Frequency	Percentage
26-35	100	50.0
36-45	92	46.0
46-54	8	4.0
Educational classification	Frequency	Percentage
Bachelors	4	2
Master's	166	83
Doctorate (Ph.D., D.D.D., D.M.D)	30	15
Years of experience	Frequency	Percentage
Less than or equal to 3 years	72	36.0
4-7 years	51	25.5
7-10 Years	45	22.5
>10 years	32	16.0
Dental specialisation	Frequency	Percent
Endodontics	15	7.5
General Dentistry	58	29
Oral and Maxillofacial Surgery	8	4
Oral Pathology	7	3.5
Orthodontist	29	14.5
Paediatric Dentistry	18	9
Periodontist	75	22.5
Prosthodontist	20	10
Dental Fields with AI Implementation	Frequency	Percent
Automated Appointments	8	4
Endodontist (root canal diagnostic)	37	18.5
Oral and Maxillofacial Surgery	23	11.5
Oral Pathology	3	1.5
Orthodontist	68	34
Periodontist (gum disease detection)	14	7
Prosthodontist	35	17.5
Radiology (dental X-rays and images)	12	6

Structural Equation Modelling

SEM, a popular multivariate analysis technique, has been used to determine the relationship among variables. i.e. Impact of Perceived ease of use and perceived usefulness on attitude to adopt AI in dentistry, which leads to behavioural intention instigating Actual usage of AI. Considering measurement errors, SEM has been employed to measure all the dependent and independent variables, where majority of the methods may not estimate measurement error (Sardeshmukh & Vandenberg, 2017).

Table 2. KMO Bartlett's statistics.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.771
Bartlett's Test of Sphericity	Approx. Chi-Square	2790.388
	df	190
	Sig.	0.000

The Kaiser-Meyer-Olkin (KMO) measure of 0.771 in Table 2 indicates a good level of sampling adequacy for factor analysis, suggesting that the dataset is suitable for structure detection.

Table 3. Communalities

Communalities		
	Initial	Extraction
PU_1 [AI-powered diagnostic tools are essential for identifying complex dental conditions accurately.]	1.000	0.727
PU_2 [AI enhances the predictive capabilities for long-term dental health planning.]	1.000	0.512
PU_3 [The integration of AI in dental imaging provides more precise and detailed results.]	1.000	0.731
PU_4 [The use of AI in dental practice supports continuous improvement in patient care through data analysis and feedback.]	1.000	0.741
EU_1 [AI applications make it easier to schedule and manage dental appointments.]	1.000	0.707
EU_2 [AI technology helps dentist quickly and accurately diagnose dental issues.]	1.000	0.739
EU_3 [AI systems make it easy to understand the breakdown of dental treatment costs.]	1.000	0.681
EU_4 [AI-assisted diagnostic tools provide quicker results compared to traditional methods.]	1.000	0.507
ATT_1 [Open to having AI-assisted technologies as part of regular dental check-ups.]	1.000	0.797
ATT_2 [Agree to choose dental clinic that uses AI technology over one that does not.]	1.000	0.679
ATT_3 [Prefer AI-assisted dental procedures for the potential to minimize human error.]	1.000	0.508
ATT_4 [AI can help in better monitoring and management of dental health over time.]	1.000	0.683
BI_1 [Rely on AI technologies to track and improve dental health.]	1.000	0.727
BI_2 [Inclined to try new AI technologies for dental care.]	1.000	0.846
BI_3 [Plan to recommend AI technology to colleagues for improving practice management.]	1.000	0.845
BI_4 [Stay updated on the latest advancements and research related to AI in dentistry]	1.000	0.702
AU_1 [AI tools are likely to be key in patient record management.]	1.000	0.794
AU_2 [AI use is likely to notably reduce administrative workload.]	1.000	0.550
AU_3 [AI is likely to assist in planning treatments for patients.]	1.000	0.570
AU_4 [AI-powered diagnostics are there to reduce costs from misdiagnosis]	1.000	0.756
Extraction Method: Principal Component Analysis.		

In the present study, the effectiveness of artificial intelligence (AI) in dental practice was evaluated using variables with varying representations in the Principal Component Analysis (PCA). The analysis revealed that certain variables demonstrated high communalities, indicating a strong alignment with the underlying factors identified in the model. For example, as shown in Table 3, the variable *"Inclined to try new AI technologies for dental care"* (0.846) reflects a strong relevance, suggesting that openness and willingness to adopt AI innovations are key drivers in the integration of AI within dental settings. Conversely, variables with lower communalities, such as *"AI-assisted diagnostic tools provide quicker results"* (0.507), suggest that these aspects are less effectively captured by the current model. This disparity highlights the need for further refinement of the model or additional research to better understand perceptions of efficiency and performance in AI-supported dental procedures. Overall, these findings emphasize the importance of examining both high- and low-loading variables to gain a more comprehensive view of how AI technologies are perceived and utilized in modern dental practice.

Table 4. Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.187	40.936	40.936	8.187	40.936	40.936
2	2.425	12.127	53.063	2.425	12.127	53.063
3	1.527	7.634	60.697	1.527	7.634	60.697
4	1.384	6.922	67.618	1.384	6.922	67.618
5	1.100	5.499	73.118	1.100	5.499	73.118
6	.870	4.351	77.469			
7	.785	3.926	81.394			
8	.709	3.545	84.939			
9	.537	2.685	87.624			
10	.466	2.332	89.956			
11	.413	2.064	92.020			
12	.389	1.944	93.964			
13	.270	1.349	95.313			
14	.217	1.086	96.399			
15	.191	.957	97.356			
16	.165	.827	98.182			
17	.137	.685	98.868			
18	.094	.472	99.340			
19	.069	.347	99.686			
20	.063	.314	100.000			
Extraction Method: Principal Component Analysis.						

The analysis presented in Table 4 shows that the first five components collectively explain a cumulative total of 73.118% of the overall variance in the dataset. This indicates that these components are the most significant in capturing the underlying structure and relationships among the variables. By explaining a substantial portion of the variance, these components provide a strong basis for interpreting key patterns and trends within the data. In contrast, the remaining components contribute progressively less to the explained variance, with their incremental contributions diminishing as the component number increases. This pattern is commonly used as a criterion for determining the optimal number of components to retain in Principal Component Analysis (PCA), ensuring that the analysis remains both parsimonious and meaningful while preserving the most informative aspects of the dataset.

Table 5 presents the Rotated Component Matrix derived from the Principal Component Analysis (PCA) using Varimax rotation, which provides a clear depiction of the relationships between AI-related attributes in dentistry and their distribution across five distinct components. These components collectively highlight the primary thematic areas of AI application in dental practice. Specifically, they emphasize the role of AI in enhancing administrative efficiency, improving diagnostic accuracy, optimizing treatment planning and fidelity, and supporting evidence-based decision-making processes within clinical workflows. Furthermore, the components illustrate the importance of driving innovation and technological advancement while ensuring the seamless integration of AI tools into routine dental operations. By categorizing these attributes into well-defined components, the analysis not only captures the structural complexity of AI implementation but also facilitates a deeper understanding of its multifaceted impact. This framework provides meaningful insights into how dental professionals perceive and engage with AI technologies, reflecting both operational improvements and clinical advancements. Such findings can guide future strategies for promoting effective AI adoption and maximizing its potential in advancing modern dental care.

Table 5: Rotated Component Matrix

	Component				
	1	2	3	4	5
AI-powered tools are essential for identifying complex dental conditions.				.685	
AI enhances the predictive capabilities for long-term dental health.				.784	
The integration of AI in dental imaging provides more precise diagnostics.				.642	
The use of AI in dental practice supports continuous improvement.				.859	
AI applications make it easier to schedule and manage dental appointments.	.610				
AI technology helps dentists to accurately diagnose dental conditions.	.892				
AI systems make it easier to understand the breakdown of dental issues.	.587				
AI-assisted tools provide quicker results compared to traditional methods	.747				
Open to having AI-assisted technologies as part of regular dental care.			.567		
Prefer dental clinics that use AI technology over those that do not.			.788		
Prefer AI-assisted dental procedures for the potential to minimize errors.			.871		
AI can help in better monitoring and management of dental health.			.673		
Rely on AI technologies to track and improve dental health.		.715			
Inclined to try new AI technologies for dental care.		.561			
Plan to recommend AI technology to colleagues for improving practice.		.563			
Stay updated on the latest advancements related to AI		.756			
AI tools are key in-patient record management.					.778
AI use is notable for reducing administrative workload.					.696
AI is useful for assisting in planning treatments for patients.					.724
AI-powered diagnostics are effective in reducing costs from misdiagnosis.					.755

Reference: Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Table 6. Convergent and discriminate Validity

	CR	AVE	MSV	MaxR(H)	Beh_Int	Per_Use	Ease_Use	Attitude	Actual Usage
Behavioural Intention	0.874	0.639	0.513	0.920	**0.799**				
Perceived Usefulness	0.712	0.661	0.293	0.725	0.418	**0.555**			
Ease of Use	0.772	0.664	0.776	0.797	0.678	0.407	**0.844**		
Attitude	0.794	0.699	0.908	0.873	0.683	0.374	0.815	**0.953**	
Actual Usage	0.757	0.648	0.908	0.828	0.716	0.541	0.881	0.836	**0.805**

Table 6 provides the reliability metrics and validity for the constructs. It can be observed that the CR criterion is located at the range from 0.712(Perceived Usefulness) to 0.874(Behavioural Intention) that is higher above the cut-off value 0.70 (Hair et al., 2020). This implies that there is a good internal consistency and reliability (CRs > 0.800) as well as good convergent validity (AVE greater than a threshold of the 0.500 as in the case of current model AVEs above 0.700 for constructs). Also, this Maximum Reliability should exceed the Minimum Significant Value (Sideridis et al., 2018). In this model, the above 0.700 and greater than the MSV Values indicate strong discriminant validity.

Table 7. Model fit statistics

Model Fit Summary				
CMIN				
Model	NPAR	CMIN	DF	CMI/DF
Default model	44	766.129	166	4.61523494
RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
Default model	0.017	0.932	DF	

Model fit statistics assess how well statistical models align with input data. A goodness-of-fit index above 0.800 indicates a strong fit (Byrne, 2013), and the current model achieved 0.932, confirming excellent adequacy. As shown in Table 7, the Root Mean Residual (RMR) is below 0.050, further validating the model. Moreover, a one-unit increase in perceived use corresponds to a 0.139-unit rise in attitude scores (p = 0.016), with a standardized estimate of 0.161, indicating a moderate effect size.

Table 8. Structural relationship

			Unstd Estimate	Std Estimate	P	Result
Attitude	<---	Perceived Usefulness	0.139	0.161	0.016	Reject
Attitude	<---	Ease of Use	0.808	0.862	***	Accept
Behavioral intention	<---	Attitude	0.404	0.889	***	Accept
Actual Usage	<---	Behavioral Intention	0.742	0.911	***	Accept
PU_4	<---	Perceived _Use	1	0.739		
PU_3	<---	Perceived _Use	0.537	0.372	***	Accept
PU_2	<---	Perceived _Use	0.582	0.394	***	Accept
PU_1	<---	Perceived _Use	0.662	0.626	***	Accept
EU_4	<---	Ease of Use	1	0.556		
EU_3	<---	Ease of Use	0.867	0.621	***	Accept
EU_2	<---	Ease of Use	0.124	0.721	***	Accept
EU_1	<---	Ease of Use	0.479	0.794	***	Accept
ATT_4	<---	Attitude	1	0.671		
ATT_3	<---	Attitude	0.904	0.591	***	Accept
ATT_2	<---	Attitude	0.768	0.588	***	Accept
ATT_1	<---	Attitude	0.284	0.875	***	Accept
BI_1	<---	Behehavioural_Intention	1	0.789		
BI_2	<---	Behehavioural_Intention	0.251	0.767	***	Accept
BI_3	<---	Behehavioural_Intention	0.233	0.808	***	Accept
BI_4	<---	Behehavioural_Intention	0.143	0.656	***	Accept
AU_1	<---	Actual_Usage	1	0.637		
AU_2	<---	Actual_Usage	0.827	0.593	***	Accept
AU_3	<---	Actual_Usage	0.917	0.627	***	Accept
AU_4	<---	Actual_Usage	0.265	0.826	***	Accept

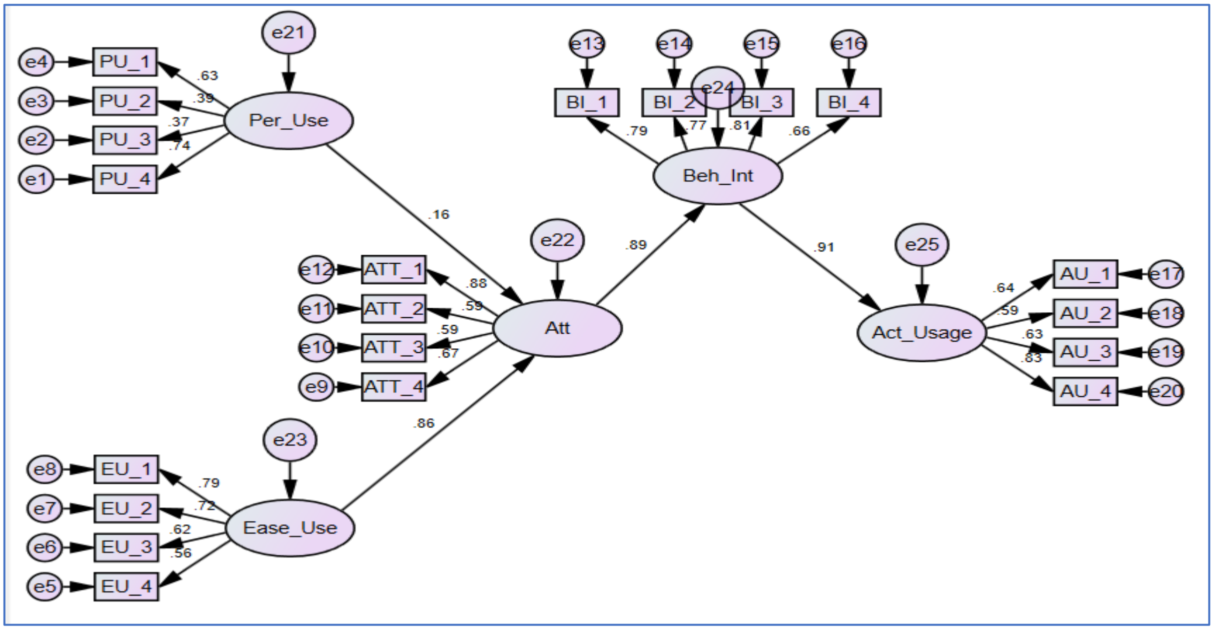

Figure 2. SEM Model

Structural Path Analysis

The proposed SEM model in Figure 2, which passed the validity and reliability tests as shown in the confirmatory factor analysis, will now progress to examining the connections between Perceived Usefulness, Perceived Ease of Use, Attitude, Behavioural Intention, and Actual Usage using the outlined structural model. The results from the structural relationship Table 8 reveal that 3 out of the 4 hypotheses (H2, H3, H4) were supported. However, Hypothesis H1 was not supported as the relationship between Perceived Usefulness and Attitude did not show a positive and significant impact, indicating no strong influence of Perceived Usefulness on Attitude to use AI in dentistry. Perceived Ease of Use ($b=0.862$, $p<0.001$), Behavioural Intention ($b=0.889$, $p<0.001$) and Actual Usage ($b=0.911$, $p<0.001$) are the components of the model having statically influence on Attitude, Behavioural Intention and Actual Usage.

Discussion

The advancement of Information Technology has offered myriads of opportunities in modern dentistry. AI has become one of the available technology which has been changing one or more aspects of oral health care. Taking into account that, the present research explores dentists' attitudes and perceptions on using AI in dentistry. According to (Ahmed et al., 2021), it establishes that AI implementation is mainly present and especially justified in Orthodontics, as 34% dentists are using it. This is based on the theoretical framework of Technology Acceptance Model (TAM) to evaluate dentists' perception towards adoption of AI in the dentistry. In certain areas like Endodontics 18.5% and Prosthodontics 17.5%, it is used for improving the quality of diagnosis and treatment without disturbing the routine operational activities.

The findings indicate that dentists' attitudes towards AI adoption are the result of perceived ease of use that influence dentists to adopt AI for diagnosis and treatment. The aim to adopt AI completely in dentistry is a result of the positive attitude of dental clinical practitioners that positively impacts its actual usage in routine practice. The findings support the TAM framework that explains dentists' attitude towards AI integration as the result of their perception of how easily they can use AI technology for diagnosis and treatment. The study findings are in line with the study of (Alhashmi et al., 2019) who explained that behavioural intentions to use AI in healthcare are dependent on the perceived ease of use of the AI technology. The results explain a strong association between attitude leading to behavioural intentions to use AI and increasing the likelihood of using it in dentistry on a regular basis. The study is supported by previous studies (Fayad & Paper, 2015; Helia et al., 2018) which explained the significant influence of positive attitude on the actual usage of AI in healthcare sector. The study highlights several benefits of how easy dentists believe AI integration is in dentistry. The dentists perceive that AI integration will help them in diagnosing more accurately and improve the overall efficiency of dental clinics. They perceive that AI integration will support scheduling and managing appointments much faster and more accurately compared to human intervention. The results are in line with the study of (Eiam-o-pas et al., 2022) who stressed that offering personalized services is possible through AI, creating better dental experiences with dentists. Dentists concerns about the reliability of data generated through AI can be addressed by reading about the latest developments in the field of AI and following the instructions about AI usage to build confidence in AI assisted diagnosis and treatment (Dashti et al., 2024). The study affirms that dentists do have a positive perception about the application of AI in dentistry for various purposes such as maintaining patient's record, planning and scheduling treatment and reliable diagnosis which will reduces the risk of committing errors in manual diagnosis. This result is in line with the previous study that explained the benefits of AI assisted diagnosis which reduces the risk of misdiagnosis when dealing with large number of patients (Ding et al., 2023; Singh et al., 2023).

Behavioral intention (BI) emerged as a critical mediator between attitudes and actual usage, reinforcing TAM's proposition that intention bridges the cognitive and actionable phases of technology adoption. Previous studies have demonstrated similar results in healthcare, where strong behavioral intentions significantly influenced the consistent use of innovative tools (Chao, 2019; Kelly et al., 2023). This highlights the importance of creating environments and strategies that encourage positive attitudes, thereby translating into actionable intentions and usage.

Finally, the study found that there is a negative and insignificant association between the perceived usefulness of dentistry in AI and their attitudes towards AI. The findings are contrary to (Alhashmi et al., 2019) who found a positive relationship between perceived usefulness and attitudes of dentists toward AI in dentistry. This suggests that, though the dentists recognize the benefits of AI integrated diagnostics, some of the practical concerns such as privacy of patients (Srivastava et al., 2023) lack of availability, validity of data and cost to integrate might influence their attitudes (Ghaffari et al., 2024; Hung et al., 2020). Hence addressing these concerns are important to fully harness AI's potential in dentistry. Future research is needed to develop approaches to address them, potentially enhancing the acceptance and application of AI in dentistry.

Several insights draw the attention of stakeholders inclined towards increasing the use of AI in dentistry. The most critical factor in the adoption of AI by dentists is the user interface that would offer ease of use and catalyse the usage rate (Ahmed et al., 2021). Apart from this, the other significant factors that restrict the adoption should be addressed, such as high initial investment cost, data accuracy, and data privacy that can be bought through robust clinical trials and data security protocols (Ghaffari et al.,2024). An additional approach to integrating AI into everyday practice might involve making AI technology more affordable and establishing a standard protocol along with straightforward demonstrations for dentists operating mid-sized clinics. This could increase their confidence in relying on technology for diagnostic purposes. Further, developing AI solutions to cater to specific needs in different sub-fields of dental healthcare, such as endodontics, orthodontics, and prosthodontics, will ensure increased use of AI in dentistry (Patil et al., 2022) and Shan et al.,2021). Domain-specific AI tools customized to specific applications, will ensure increased adoption and usage. The findings of this study highlight the need for technological integration through user-centric AI design development catering to domain-specific requirements through effective demonstration and addressing obstacles, thus encouraging its application in dentistry.

Conclusion

The study emphasizes the transformative role of AI in dentistry, supported by the Technology Acceptance Model (TAM). The findings suggest that although dentists are aware of the benefits of AI in dentistry, a strong belief in its usefulness did not lead to any positive change in their attitudes toward integrating AI in their daily practice. This indicates that though dental professionals' find AI easy to use, they might not find it essential. The study also found that the overall attitude towards AI adoption did not vary significantly across different dental specializations, suggesting an undeviating insight across various fields within dentistry. Looking forward, in the near future the potential for AI in dentistry appears promising, with notable opportunities for significant growth in various areas such as predictive diagnostics, tailored treatment approaches, and patient management systems. Incessant advancements in AI technologies promise to further revolutionize dental practices, making them more effective and patient-centric. Nevertheless, for sustained growth and acceptance, continuous research and development, informative training programs for dental professionals and increased awareness about the merits and limitations of AI are essential. This will ensure that AI tools are used effectively and ethically, aligning with the evolving needs of the dental industry. Future research should explore key areas to facilitate the effective adoption of AI in dentistry. One such crucial area is adoption in rural or underserved regions where the problems like limited infrastructure, lack of skilled professionals, resistance to technological changes may impede the implementation. Additional studies concerning to cultural or systemic barriers to AI acceptance must be examined, as apprehension about manpower reduction, Lack of trust in AI decision-making, and ethical reflections connected to data privacy may limit adoption. Another important emphasis is the cost-effectiveness of AI tools in dentistry, as considerable upfront cost can be a implementation barrier for many dental practitioner. Bridging these research gaps will provide a complete understanding of AI's role in dentistry and ensuring its ethical and effective implementation.

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Author contributions
Dr. Rizwana played an essential role in conceptualizing the framework of the study and designing the research methodology. **Dr. Padmalini Singh** meticulously carried out quantitative analysis using SPSS, AMOS. **Dr.Shubha Muralidhar** was instrumental in overseeing the research process and carried out the complete review, reference checking and proof reading. Together, the combined efforts of all the authors ensured a comprehensive exploration of the topic and contributing significantly to the scholarly discourse. **Pompi Roy** contributed to interpreting the findings and strengthening the discussion.

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