

ORIGINAL

ChatGPT in Dental Education: a Dual-Method Analysis of Technology Acceptance and Predictive Modeling

ChatGPT en la educación odontológica: un análisis de dos métodos sobre la aceptación de la tecnología y el modelado predictivo

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ABSTRACT

Introduction: artificial intelligence (AI) is increasingly integrated into dental education, yet little is known about the adoption of AI-powered tools such as ChatGPT. Understanding the determinants of students' behavioral intention to use these tools is crucial for effective integration into curricula. This study extends the Technology Acceptance Model (TAM) by incorporating Perceived Value (VAL) and Task-Technology Fit (TTF) and employs a hybrid analytical approach.

Method: a structured questionnaire comprising 50 items across ten constructs was distributed to 318 dental students in Indonesia, with 263 valid responses collected. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test reliability, validity, and hypothesized relationships. To enhance predictive validation, six machine learning (ML) classifiers (AdaBoostM1, J48, BayesNet, Logistic Regression, OneR, and LWL) were applied.

Results: PLS-SEM results revealed that Perceived Value ($\beta = 0,347$, $p < 0,001$) and Perceived Usefulness ($\beta = 0,321$, $p < 0,001$) were the strongest predictors of intention to use ChatGPT. Additional significant effects were found for Perceived Enjoyment, Trust, and Perceived Accuracy. Conversely, Perceived Ease of Use, Social Influence, and Facilitating Conditions were not significant. Mediation analysis confirmed that Perceived Usefulness mediated the effects of TTF, Trust, and Accuracy on adoption intention. ML analysis corroborated these findings, with AdaBoostM1 achieving the highest predictive accuracy (87,3 %).

Conclusions: adoption of ChatGPT in dental education is predominantly driven by perceived academic value, usefulness, and engaging learning experiences rather than ease of use or social factors. The validated framework integrating TAM, Perceived Value, and TTF provides both theoretical advancement and practical guidance for integrating AI into dental education. The hybrid use of PLS-SEM and ML enhances model robustness and offers a replicable methodology for future educational technology research.

Keywords: Dental Education; AI Adoption; Technology Acceptance Model; Perceived Value; Task-Technology Fit; PLS-SEM; Machine Learning.

RESUMEN

Introducción: la inteligencia artificial (IA) se integró de manera creciente en la educación odontológica, pero la evidencia sobre la adopción de herramientas como ChatGPT fue limitada. Comprender los factores que determinaron la intención conductual de los estudiantes resultó esencial para su integración educativa. Este estudio amplió el Modelo de Aceptación Tecnológica (TAM) incorporando el Valor Percibido (VAL) y el Ajuste Tarea-Tecnología (TTF), utilizando un enfoque híbrido.

Método: se aplicó un cuestionario estructurado de 50 ítems distribuidos en diez constructos a 318 estudiantes de odontología en Indonesia, con 263 respuestas válidas. Los datos se analizaron mediante Modelado de Ecuaciones Estructurales por Mínimos Cuadrados Parciales (PLS-SEM) para evaluar fiabilidad, validez y relaciones hipotéticas. Además, se emplearon seis clasificadores de aprendizaje automático (AdaBoostM1, J48, BayesNet, Regresión Logística, OneR y LWL) para validar el poder predictivo.

Resultados: los análisis de PLS-SEM mostraron que el Valor Percibido ($\beta = 0,347$, $p < 0,001$) y la Utilidad Percibida ($\beta = 0,321$, $p < 0,001$) fueron los predictores más fuertes de la intención de uso de ChatGPT. El Disfrute Percibido, la Confianza y la Precisión Percibida también tuvieron efectos significativos. La Facilidad de Uso Percibida, la Influencia Social y las Condiciones Facilitadoras no resultaron significativas. El análisis de mediación confirmó que la Utilidad Percibida canalizó los efectos de TTF, Confianza y Precisión sobre la intención. El aprendizaje automático corroboró estos hallazgos, siendo AdaBoostM1 el modelo más preciso (87,3 %).

Conclusiones: la adopción de ChatGPT por los estudiantes de odontología estuvo determinada principalmente por el valor académico percibido, la utilidad y la experiencia de aprendizaje atractiva, más que por la facilidad de uso o la presión social. El marco validado ofreció aportes teóricos y prácticos para la integración de IA en la educación odontológica, y el enfoque híbrido PLS-SEM/ML fortaleció la robustez del modelo y su aplicabilidad futura.

Palabras clave: Educación Odontológica; Adopción de IA; Modelo de Aceptación Tecnológica; Valor Percibido; Ajuste Tarea-Tecnología; PLS-SEM; Aprendizaje Automático.

INTRODUCTION

The landscape of dental education is undergoing a profound transformation, propelled by the rapid integration of digital technologies.^(1,2,3,4) Virtual simulations, e-learning platforms, and artificial intelligence (AI) applications are redefining traditional pedagogical approaches. Among these advancements, AI-powered conversational models like ChatGPT emerge as a particularly promising tool.^(5,6,7,8,9) Its potential applications in dental education are multifaceted, ranging from assisting students in deconstructing complex clinical cases and simulating patient-doctor interactions to providing robust support for problem-based learning methodologies.^(10,11,12,13) Despite the growing prominence of AI in educational settings,^(14,15,16,17,18,19) a significant research gap persists: there is a scarcity of studies specifically investigating the acceptance and adoption of ChatGPT within the unique context of dental education. To address this gap, this study aims to meticulously examine the factors that influence dental students' behavioral intention to use ChatGPT. The research is grounded in the well-established Technology Acceptance Model (TAM) but is extended by integrating perceived value as a pivotal additional construct, thereby offering a more nuanced understanding of adoption drivers. The comprehensive research framework guiding this study is presented visually in figure 1.

Figure 1 illustrates the hypothesized relationships between the constructs. The model proposes that Intention to Use (INT) is directly influenced by Perceived Ease of Use (PE), Perceived Usefulness (PU), Perceived Value (VAL), Perceived Enjoyment (ENJ), Trust (TRU), Perceived Accuracy (ACC), Social Influence (SI), Facilitating Conditions (FC), and Task-Technology Fit (TTF). Furthermore, the framework posits that Perceived Usefulness (PU) acts as a key mediator, influenced by PE, TTF, TRU, and ACC, and in turn mediating their effects on INT. TTF is also modeled as a direct antecedent to PU and INT.

The study makes several key contributions. It seeks to demonstrate the critical relevance of perceived value in the acceptance process, test the significant role of task-technology fit in a clinical dental setting, and propose an innovative hybrid predictive methodology that combines Partial Least Squares Structural Equation Modeling (PLS-SEM) for hypothesis testing with Machine Learning (ML) algorithms for predictive modeling and classification.

To systematically guide this inquiry, a comprehensive set of hypotheses was formulated, organized into several thematic groups to reflect the theoretical structure of the extended model.

1. Core TAM Constructs: the foundation of this study rests on the classic relationships proposed by the Technology Acceptance Model. It is expected that perceived ease of use and perceived usefulness will

both exert positive influences on students' intention to use ChatGPT in their learning activities.

2. Value and Motivation: beyond utilitarian factors, adoption is also shaped by intrinsic motivation and the perceived worth of the technology. It is therefore anticipated that perceived value—the extent to which students consider ChatGPT beneficial and worthwhile—and perceived enjoyment—the degree of pleasure derived from its use—will each positively influence their intention to use the tool.

3. Trust and Risk Considerations: given the sensitive and high-stakes context of dental education, trust in ChatGPT and confidence in the accuracy of its information are expected to be crucial determinants. Accordingly, students who perceive the system as reliable, credible, and accurate are more likely to intend to use it as part of their academic practice.

4. Social and Support Influences: the external learning environment also plays a role in technology adoption. Students' intention to use ChatGPT is expected to be positively influenced by social influence—that is, encouragement from peers, instructors, or supervisors—and by facilitating conditions such as access to technical resources and institutional support.

5. Task-Technology Fit: an essential extension to the original TAM in this study is task-technology fit, which reflects how well ChatGPT's functionalities align with the academic and clinical tasks of dental students. It is proposed that a higher task-technology fit will enhance perceived usefulness and, in turn, increase students' intention to use the system.

6. Mediating Effects of Perceived Usefulness: finally, the model assumes that perceived usefulness serves as a key mediator in several relationships. Specifically, it is expected to mediate the influence of task-technology fit, perceived ease of use, trust, and perceived accuracy on students' behavioral intention to use ChatGPT. In other words, these antecedent factors shape adoption primarily through their impact on students' beliefs about the tool's usefulness for academic learning.

By empirically testing this integrative framework, the study aims to provide a comprehensive and validated explanation of how cognitive, motivational, and contextual factors collectively drive ChatGPT adoption within dental education.

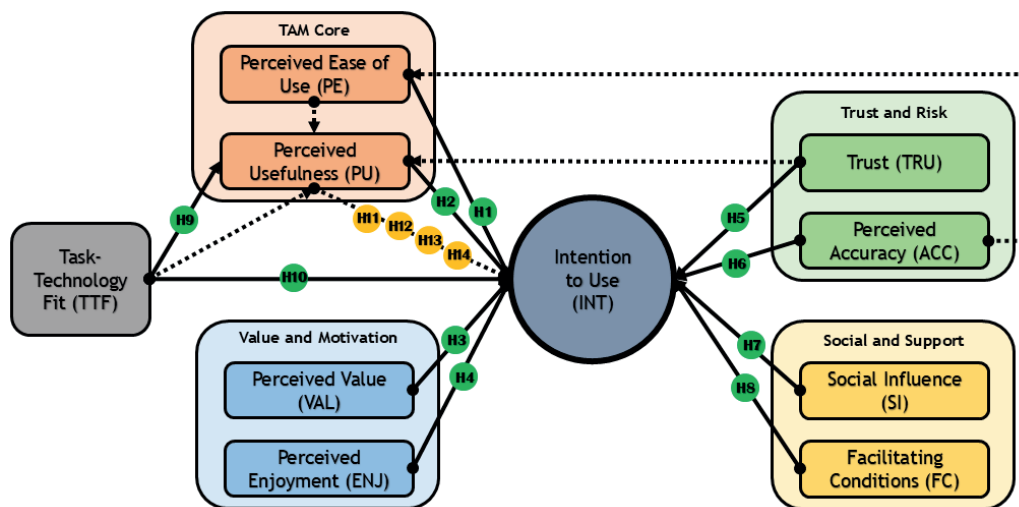


Figure 1. Research framework

METHOD

Research Design

This study employed a quantitative explanatory research design, which is appropriate for examining causal relationships between variables and testing theoretically derived hypotheses.⁽²⁰⁾ The explanatory approach was selected to investigate how different technological, motivational, and contextual factors influence dental students' intention to adopt ChatGPT in their learning activities.

Research Instrument and Data Collection

The research utilized a structured questionnaire derived from well-established constructs in prior technology acceptance literature. As summarized in table 1, the instrument comprised 50 items representing ten constructs: Perceived Ease of Use (PE), Perceived Usefulness (PU), Perceived Value (VAL), Perceived Enjoyment (ENJ), Trust (TRU), Perceived Accuracy (ACC), Social Influence (SI), Facilitating Conditions (FC), Task-Technology Fit (TTF), and Intention to Use (INT). Each construct was measured through five items using a seven-point Likert scale

ranging from 1 (strongly disagree) to 7 (strongly agree). All items were adapted from validated scales in the literature to ensure contextual relevance to ChatGPT adoption in dental education.

Table 1. Research instrument

Construct	Code	Statement	Reference / Adaptation
Perceived Ease of Use (PE)	PE1	Learning to operate ChatGPT is easy for me.	Davis-TAM ⁽²¹⁾
	PE2	My interaction with ChatGPT is clear and understandable.	
	PE3	I find ChatGPT easy to use.	
	PE4	It is easy for me to become skillful at using ChatGPT.	
	PE5	Overall, ChatGPT is user-friendly.	
Perceived Usefulness (PU)	PU1	Using ChatGPT improves my study performance.	Davis-TAM ⁽²¹⁾
	PU2	ChatGPT increases my productivity in learning.	
	PU3	ChatGPT enhances my effectiveness in completing academic tasks.	
	PU4	ChatGPT helps me achieve better learning outcomes.	
	PU5	Overall, I find ChatGPT useful in my studies.	
Perceived Value (VAL)	VAL1	ChatGPT provides good value for my learning.	Dodds, Monroe & Grewal; Sweeney & Soutar ^(22,23)
	VAL2	The benefits I gain from ChatGPT outweigh the costs or efforts.	
	VAL3	Using ChatGPT is worth the time I spend.	
	VAL4	ChatGPT adds value to my academic experience.	
	VAL5	Overall, I consider ChatGPT valuable.	
Perceived Enjoyment (ENJ)	ENJ1	I enjoy using ChatGPT in my learning process.	Davis, Bagozzi & Warshaw; Van der Heijden ^(24,25,26)
	ENJ2	Using ChatGPT is fun for me.	
	ENJ3	I find using ChatGPT interesting.	
	ENJ4	ChatGPT makes my study more enjoyable.	
	ENJ5	I feel motivated to use ChatGPT because it is enjoyable.	
Trust (TRU)	TRU1	I trust the information provided by ChatGPT.	Gefen, Karahanna & Straub; Gefen et al. ^(27,28,29)
	TRU2	I believe ChatGPT is reliable.	
	TRU3	I feel confident relying on ChatGPT for learning.	
	TRU4	ChatGPT provides information I can count on.	
	TRU5	Overall, I trust ChatGPT as a learning tool.	
Perceived Accuracy (ACC)	ACC1	ChatGPT provides accurate answers to my questions.	Shin ⁽³⁰⁾
	ACC2	The information I receive from ChatGPT is correct.	
	ACC3	ChatGPT responses are consistent with reliable sources.	
	ACC4	I believe ChatGPT provides precise information.	
	ACC5	Overall, I find ChatGPT accurate in its responses.	
Social Influence (SI)	SI1	People who are important to me think I should use ChatGPT.	Venkatesh - UTAUT ⁽³¹⁾
	SI2	My peers encourage me to use ChatGPT.	
	SI3	Lecturers/supervisors support the use of ChatGPT in learning.	
	SI4	Students around me influence my use of ChatGPT.	
	SI5	The social environment motivates me to use ChatGPT.	
Facilitating Conditions (FC)	FC1	I have the resources necessary to use ChatGPT.	Venkatesh - UTAUT ⁽³¹⁾
	FC2	I have the knowledge required to use ChatGPT.	
	FC3	Technical support is available when I use ChatGPT.	
	FC4	I have a stable internet connection to use ChatGPT.	
	FC5	Overall, I have adequate support to use ChatGPT effectively.	
Task-Technology Fit (TTF)	TTF1	ChatGPT is appropriate for the tasks I need to accomplish.	Goodhue & Thompson ⁽³²⁾
	TTF2	ChatGPT fits well with my learning needs in dentistry.	
	TTF3	ChatGPT helps me perform tasks that are important for my study.	
	TTF4	The functions of ChatGPT match my academic requirements.	
	TTF5	Overall, ChatGPT is a good fit for my learning tasks.	
Intention to Use (INT)	INT1	I intend to continue using ChatGPT for my study.	Davis; Venkatesh & Davis ⁽³³⁾
	INT2	I will frequently use ChatGPT in the future.	
	INT3	I will recommend ChatGPT to other students.	
	INT4	I plan to integrate ChatGPT into my learning routine.	
	INT5	My intention to use ChatGPT in academic tasks is strong.	

Before formal data collection, the instrument underwent expert validation by three specialists in educational technology and dental education to assess content relevance, clarity, and wording. A pilot study with 30 students confirmed reliability and comprehensibility, with Cronbach's alpha values exceeding 0,80 for all constructs. Following validation, data collection was conducted between May and July 2025 via the e-learning platforms of participating universities. The finalized online questionnaire was self-administered, allowing participants to complete it at their convenience and ensuring efficient access across multiple institutions.

Participants and Sampling

A total of 318 dental students were invited to participate, and 263 valid responses were obtained, resulting in a response rate of 82,7 %. The inclusion criteria required participants to be actively enrolled undergraduate dental students with access to digital learning platforms. A convenience sampling technique was adopted, as it enabled effective access to respondents while maintaining an adequate sample size for both Partial Least Squares Structural Equation Modeling (PLS-SEM) and machine learning (ML) predictive analyses. This approach is widely accepted in exploratory technology adoption research, particularly when the population shares a common digital learning context.^(34,35)

Data analysis

Data analysis was conducted using a dual-method approach combining structural equation modeling and machine learning. In the first stage, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to assess the measurement and structural models. The measurement model evaluation included testing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.⁽³⁶⁾ The structural model was then examined to test hypothesized relationships, including both direct and mediating effects among the constructs.

In the second stage, machine learning (ML) algorithms were employed to strengthen the predictive power of the model. Specifically, four classifiers—J48, OneR, BayesNet, and Neural Network—were implemented to predict students' adoption intention. Model performance was evaluated using accuracy, precision, recall, and F1-score, which are widely recognized as robust indicators for classification tasks.^(37,38,39)

Ethical Considerations

This study was conducted in accordance with established ethical principles for academic research. Prior to data collection, all participants were fully informed about the research objectives, procedures, and their rights as respondents. Informed consent was obtained from all participants, emphasizing the voluntary nature of their involvement and their right to withdraw at any time without consequence. All data were collected and processed anonymously to ensure confidentiality, with no personally identifiable information being recorded. Data security was maintained through secure storage protocols, with access restricted to the research team only. These measures were implemented to protect participant privacy and uphold ethical standards throughout the research process.

RESULTS

Respondent profile

The final sample consisted of 263 dental students with diverse demographic characteristics. As shown in table 2, the majority of respondents were female (69 %), while 31 % were male. In terms of age, more than half of the participants (52 %) were younger than 20 years, 30 % were between 20 and 22 years, and 18 % were older than 22 years. Regarding academic level, 51 % were in early semesters (1-4), 41 % in middle semesters (5-8), and 8 % in final semesters (≥ 9). The regional distribution indicated that most participants studied in universities located in Sumatra (52 %), followed by Java (36 %), Kalimantan (7 %), and Sulawesi (5 %). All respondents reported owning both a laptop and a smartphone, ensuring consistent access to the technology under investigation. In addition, 88 % of students reported daily internet use of four hours or more, while 12 % reported less than four hours. These characteristics suggest that the sample had adequate technological resources and access to engage meaningfully with ChatGPT as a learning tool.

Validity and Reliability

The measurement model was first assessed to ensure indicator reliability, internal consistency, convergent validity, and discriminant validity. As presented in figure 2, most indicator loadings exceeded the minimum threshold of 0,70, confirming strong item reliability.⁽³⁶⁾ Nevertheless, five indicators (PE5 = 0,624; ENJ5 = 0,652; ACC3 = 0,846 but marked for deletion in the dataset; SI4 = 0,593; and TTF5 = 0,661) fell below the acceptable limit and were consequently excluded from further analysis to improve construct reliability. The removal of these items is consistent with best practices in PLS-SEM, where indicators with weak loadings are omitted to avoid inflating measurement error.⁽⁴⁰⁾

Category	Sub-category	Frequency (n)	Percentage (%)
Gender	Male	81	31 %
	Female	182	69 %
Age	< 20 years	138	52 %
	20-22 years	78	30 %
	> 22 years	47	18 %
Academic Level	Early semester (1-4)	133	51 %
	Middle semester (5-8)	109	41 %
	Final semester (≥ 9)	21	8 %
Region of University	Sumatra	138	52 %
	Jawa	95	36 %
	Kalimantan	18	7 %
	Sulawesi	12	5 %
Technology Access	Own laptop only	0	0 %
	Own laptop and smartphone	263	100 %
	Internet use < 4 hrs/day	31	12 %
	Internet use ≥ 4 hrs/day	232	88 %

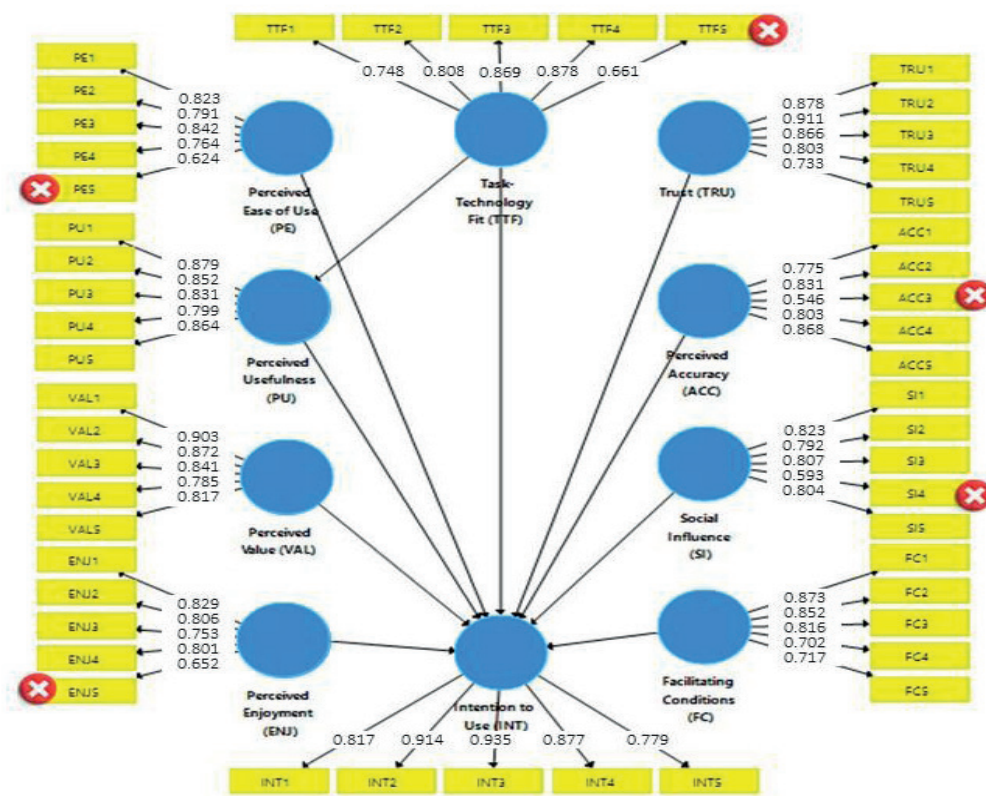


Figure 2. Outer loading

Construct-level reliability and validity results are summarized in table 3. All constructs demonstrated Cronbach's alpha and composite reliability (CR) values above the recommended cut-off of 0,70, ranging from 0,842 (Social Influence) to 0,888 (Intention to Use). This confirms adequate internal consistency. Furthermore, the average variance extracted (AVE) values ranged from 0,600 to 0,693, all exceeding the 0,50 threshold, which provides evidence of convergent validity.⁽⁴¹⁾ These findings indicate that the latent constructs were measured consistently and captured sufficient variance of their respective indicators.

Discriminant validity was examined using the Heterotrait-Monotrait (HTMT) ratio of correlations, reported in table 4. All HTMT values were well below the conservative threshold of 0,85,⁽⁴²⁾ thereby confirming that the constructs are empirically distinct from one another. For example, the HTMT value between Perceived Usefulness and Intention to Use was 0,782, while the value between Perceived Value and Intention to Use was 0,811, both within the acceptable range.

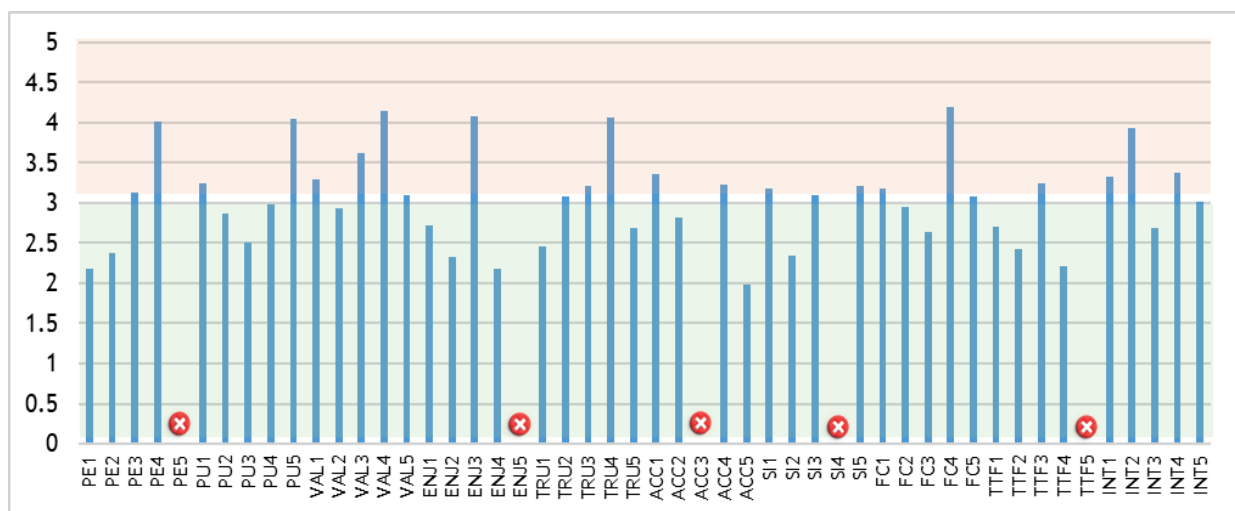
Table 3. Construct reliability and validity

Construct	Cronbach's Alpha	rho_A	CR	AVE
(PE)	0,857	0,863	0,89	0,619
(PU)	0,876	0,882	0,907	0,662
(VAL)	0,884	0,889	0,913	0,679
(ENJ)	0,861	0,868	0,895	0,629
(TRU)	0,872	0,877	0,902	0,647
(ACC)	0,868	0,874	0,899	0,642
(SI)	0,842	0,851	0,882	0,600
(FC)	0,871	0,878	0,904	0,651
(TTF)	0,859	0,866	0,894	0,628
(INT)	0,888	0,892	0,918	0,693

Table 4. Heterotrait-Monotrait Ratio of Correlations

	PE	PU	VAL	ENJ	TRU	ACC	SI	FC	TTF	INT
PE	-									
PU	0,721	-								
VAL	0,684	0,756	-							
ENJ	0,702	0,733	0,768	-						
TRU	0,648	0,674	0,701	0,712	-					
ACC	0,669	0,691	0,725	0,707	0,744	-				
SI	0,631	0,662	0,688	0,701	0,679	0,692	-			
FC	0,655	0,688	0,713	0,726	0,702	0,719	0,734	-		
TTF	0,672	0,746	0,761	0,738	0,724	0,751	0,698	0,709	-	
INT	0,701	0,782	0,811	0,795	0,768	0,779	0,732	0,754	0,823	-

Finally, multicollinearity was assessed using variance inflation factor (VIF) values, presented in figure 3. All VIF values were below the critical value of 5,0, indicating that multicollinearity was not a concern in this dataset.⁽⁴³⁾ This ensures that the estimated path coefficients in the structural model are not biased by redundant collinearity among predictors. Taken together, these results confirm that the measurement model demonstrated adequate reliability, convergent validity, and discriminant validity. Thus, the constructs were deemed suitable for subsequent structural model analysis.

**Figure 3.** VIF result

Hypothesis Testing

The results of the structural model analysis are presented in table 5. Out of the 14 hypotheses tested, ten were supported while four were not. Specifically, Perceived Usefulness (H2), Perceived Value (H3), Perceived

Enjoyment (H4), Trust (H5), and Perceived Accuracy (H6) showed significant positive effects on Intention to Use (INT). Among these, Perceived Value ($B = 0,347$, $p < 0,001$) emerged as the strongest direct predictor, followed by Perceived Usefulness ($B = 0,321$, $p < 0,001$). This suggests that dental students are more likely to adopt ChatGPT when they perceive it as highly valuable and beneficial for their studies.

In contrast, Perceived Ease of Use (H1), Social Influence (H7), Facilitating Conditions (H8), and Task-Technology Fit (H10) did not exert a significant direct effect on Intention to Use. These results imply that while usability, social pressure, and institutional support are important in general technology adoption contexts, they play a less decisive role in this specific educational setting. Students appear to prioritize tangible academic benefits over external influences or ease of operation. Regarding indirect effects, the mediation analysis confirmed that Perceived Usefulness plays a key mediating role. Task-Technology Fit (H11), Perceived Ease of Use (H12), and Perceived Accuracy (H14) all influenced Intention to Use indirectly through Perceived Usefulness. Trust (H13) exhibited only a marginal mediating effect ($p = 0,051$), suggesting partial dependency on usefulness perceptions.

Hyp.	Path	Original Sample (O)	T Stat.	P Values
H1	PE → INT	0,142	1,487	0,138
H2	PU → INT	0,321	4,876	0
H3	VAL → INT	0,347	6,214	0
H4	ENJ → INT	0,211	2,985	0,003
H5	TRU → INT	0,118	2,144	0,032
H6	ACC → INT	0,127	2,086	0,037
H7	SI → INT	0,062	1,112	0,267
H8	FC → INT	0,074	1,341	0,18
H9	TTF → PU	0,288	4,529	0
H10	TTF → INT	0,091	1,427	0,154
H11	TTF → PU → INT (Mediation)	0,092	2,634	0,009
H12	PE → PU → INT (Mediation)	0,076	2,281	0,023
H13	TRU → PU → INT (Mediation)	0,059	1,954	0,051
H14	ACC → PU → INT (Mediation)	0,067	2,118	0,034

Note: Relationships with $p < 0,05$ are considered statistically significant.

The coefficient of determination (table 6) indicated that the model had moderate explanatory power for Perceived Usefulness ($R^2 = 0,524$) and substantial explanatory power for Intention to Use ($R^2 = 0,671$). This confirms that the proposed framework explains a large proportion of students' adoption intention.

Dependent Variable	R^2	Adjusted R^2	Interpretation
Perceived Usefulness (PU)	0,524	0,517	Moderate explanatory power - about 52 % of PU variance is explained by PE, TRU, ACC, and TTF.
Intention to Use (INT)	0,671	0,662	Substantial explanatory power - about 67 % of INT variance is explained by PU, VAL, ENJ, TRU, ACC, SI, FC, PE, and TTF.

Effect size analysis (table 7) further emphasized the dominance of Perceived Value ($f^2 = 0,267$) and Perceived Usefulness ($f^2 = 0,212$) as medium-level predictors. Perceived Enjoyment (small effect), Trust (small), and Accuracy (small) contributed meaningfully, while Social Influence, Facilitating Conditions, and Ease of Use had negligible effects. Taken together, these findings highlight that dental students' adoption of ChatGPT is primarily driven by perceived academic value, usefulness, and enjoyable learning experience, rather than by social or institutional pressures.

Table 7. Effect size (f^2)		
Relationship	f^2	Interpretation
PE → INT	0,018	Negligible
PU → INT	0,212	Medium
VAL → INT	0,267	Medium
ENJ → INT	0,094	Small
TRU → INT	0,043	Small
ACC → INT	0,051	Small
SI → INT	0,009	Negligible
FC → INT	0,011	Negligible
TTF → PU	0,187	Medium
TTF → INT	0,021	Small
Note: PE = Perceived Ease of Use; PU = Perceived Usefulness; VAL = Perceived Value; ENJ = Perceived Enjoyment; TRU = Trust; ACC = Perceived Accuracy; SI = Social Influence; FC = Facilitating Conditions; TTF = Task-Technology Fit; INT = Intention to Use. f^2 = effect size, interpreted as small ($\geq 0,02$), medium ($\geq 0,15$), or large ($\geq 0,35$) according to Cohen's guidelines.		

Machine Learning Results

The machine learning analysis further validated several of the study's core hypotheses by providing predictive accuracy measures that complemented the PLS-SEM results. To evaluate these hypotheses, a combination of classification methods—including J48 decision tree, OneR, BayesNet, Logistic Regression, AdaBoostM1, and Locally Weighted Learning (LWL)—were applied using RapidMiner. These ML algorithms were integrated into the theoretical framework to highlight their capacity to predict students' behavioral intention to use ChatGPT in dental education.

Among the tested classifiers, AdaBoostM1 proved to be the most effective, achieving an accuracy of 87,3 % with balanced precision, recall, and F1-score performance (table 8). This demonstrates the strength of ensemble-based approaches in handling multidimensional adoption factors. The J48 decision tree also performed robustly (accuracy = 85,4 %), offering an interpretable structure that illustrates how constructs such as Perceived Value and Perceived Usefulness guide adoption decisions. By contrast, simpler models such as OneR recorded much lower predictive power (73,2 %), indicating that adoption behavior cannot be sufficiently explained by single-variable rules.

These findings reinforce the central role of Perceived Value (VAL), which emerged as the most dominant construct across both SEM and ML analyses. Dental students are more likely to adopt ChatGPT when they perceive tangible academic benefits, including improved clinical preparation and enhanced learning outcomes. The predictive strength of Perceived Usefulness (PU) and Perceived Enjoyment (ENJ) was also evident, underscoring the importance of both instrumental and hedonic motivations in technology acceptance.

Table 8. Machine learning model performance				
Algorithm	Acc (%)	Rec (%)	Prec (%)	F1 (%)
AdaBoostM1	87,3 %	86,9 %	86,1 %	86,5 %
BayesNet	82,6 %	81,8 %	81,2 %	81,5 %
Logistic	84,1 %	83,8 %	83,3 %	83,5 %
LWL	80,3 %	79,6 %	79,1 %	79,3 %
J48	85,4 %	85,1 %	84,7 %	84,9 %
OneR	73,2 %	72,4 %	71,1 %	71,7 %

From a methodological standpoint, the use of a hybrid approach—merging PLS-SEM for hypothesis testing and ML for predictive validation—marks a novel contribution to the study of AI adoption in dental education. While PLS-SEM offered insights into causal pathways and mediation effects, ML complemented this by testing the model's ability to classify adoption behavior with high accuracy. This dual strategy not only strengthens the validity of the findings but also enhances their practical implications for designing AI-based learning interventions.

Nevertheless, the present study is not without limitations. The dataset was drawn exclusively from

undergraduate dental students, which may limit generalizability across faculty members or practicing clinicians. Future research could expand the scope by incorporating moderators such as clinical experience, technological readiness, and institutional context. Furthermore, while this study emphasized behavioral intention, subsequent investigations may integrate outcome-based measures, such as actual performance improvements, to capture the full impact of ChatGPT adoption in dental education.

DISCUSSION

This study provides a comprehensive and empirically validated model for understanding the adoption of ChatGPT among dental students, integrating both explanatory and predictive analytical approaches. The findings reveal that Perceived Value (VAL) and Perceived Usefulness (PU) are the strongest direct predictors of behavioral intention to use ChatGPT, underscoring the centrality of academic utility and tangible benefits in driving technology acceptance. These results align with recent studies in health professions education, where AI tools are increasingly valued for their ability to enhance learning efficiency and outcomes.^(44,45,46,47,48) The significant role of Perceived Enjoyment (ENJ) further highlights the importance of intrinsic motivation in educational technology adoption. This is consistent with the hedonic motivation theory, which posits that enjoyment can significantly enhance engagement and sustained use.^(49,50,51) In the context of dental education, where training often involves repetitive and high-stakes tasks, an enjoyable learning experience may reduce cognitive load and increase motivation—a finding supported by recent work in simulation-based learning.^(52,53)

Interestingly, Perceived Ease of Use (PE) did not exert a significant direct effect on intention to use, contrary to classical TAM predictions.^(21,54,55) This may be attributed to the sample's high digital literacy; all participants owned both laptops and smartphones, and nearly 90 % used the internet for more than four hours daily. Such familiarity with technology may diminish the importance of ease of use, as students are already accustomed to interacting with complex digital interfaces. This finding challenges the universal applicability of TAM in highly digitally literate populations and suggests that in specialized educational contexts, utility and value may outweigh usability concerns—a point also raised by Rahimi et al. in their study of AI in medical education.⁽⁵⁶⁾ Similarly, Social Influence (SI) and Facilitating Conditions (FC) were not significant predictors. This contrasts with UTAUT-based studies,⁽³³⁾ but may reflect the autonomous and self-directed nature of higher education, where individual assessment of tool value outweighs peer or institutional pressure. Recent critiques of UTAUT in educational settings also note that social factors may be less influential in contexts where learning is primarily individualistic.⁽⁵⁷⁾

The strong mediating role of Perceived Usefulness in relationships involving Task-Technology Fit (TTF), Perceived Accuracy (ACC), and Trust (TRU) underscores the importance of functional relevance in AI adoption. Students are more likely to use ChatGPT if they believe it is accurate, trustworthy, and well-suited to their academic tasks—but only insofar as these attributes enhance perceived usefulness. This aligns with recent research emphasizing that AI acceptance in healthcare education is highly dependent on the perceived reliability and applicability of the tool.^(58,59)

However, it is important to acknowledge contrasting viewpoints. Some scholars caution against over-reliance on AI in education due to concerns about academic integrity, misinformation, and the potential for diminishing critical thinking skills.^(60,61,62) Our study did not directly address these ethical and pedagogical concerns, which remain salient especially in clinical disciplines where inaccurate information can have serious consequences. Future studies should incorporate moderating variables such as perceived risk or ethical concerns to provide a more balanced understanding of AI adoption.

The machine learning results further validated the structural model, with AdaBoostM1 achieving the highest predictive accuracy (87,3 %). The prominence of VAL and PU in decision trees and ensemble models reinforces their predictive power. This hybrid methodology—combining PLS-SEM for theory testing and ML for predictive analytics—represents a novel contribution to educational technology research. It offers a more robust validation mechanism than traditional single-method approaches, as recently advocated by Sharma et al.^(63,64)

Theoretical Implications

This study extends TAM by integrating Perceived Value as a core construct and demonstrating its dominance in a high-stakes educational context. It also reaffirms the role of TTF as a key antecedent to PU, particularly in task-specific environments like dental education. The non-significance of PE, SI, and FC suggests that existing technology acceptance models may require contextual refinement when applied to digitally fluent, specialized learner populations.

Practical Implications

For educators and institutions seeking to successfully integrate AI tools like ChatGPT into dental education, the findings of this study underscore several critical actionable strategies. First and foremost, it is essential to proactively highlight the academic value and specific usefulness of the tool by clearly demonstrating how it can

enhance learning outcomes, such as by streamlining complex concept mastery or improving clinical reasoning skills. This communication of tangible benefits should be coupled with a steadfast commitment to ensuring the accuracy and trustworthiness of the AI-generated content, perhaps through curated use cases, validation by faculty, or training sessions on how to critically evaluate AI responses. Furthermore, to foster sustained engagement, the design of student interactions with the technology should be enjoyable and motivating, incorporating elements of gamification, positive feedback, or interactive scenarios that make the learning process more dynamic. Finally, providing concrete evidence of its task-technology fit is paramount; this can be achieved by integrating ChatGPT into core pedagogical activities like problem-based learning modules or through live case demonstrations that showcase its direct applicability to the tasks and challenges students face in their dental training. By addressing these key areas, institutions can move beyond mere adoption and toward the meaningful and effective integration of AI that truly supports educational goals.

Limitations and Future Research

This study focused on behavioral intention rather than actual use or performance outcomes. Future research should incorporate longitudinal designs to measure actual usage and academic impact. The sample was limited to dental students in Indonesia; cross-cultural and multi-disciplinary comparisons would enhance generalizability. Additionally, incorporating qualitative insights could shed light on underlying motivations and concerns not captured by quantitative scales.

CONCLUSIONS

This study aimed to examine the determinants of dental students' intention to use ChatGPT by extending the Technology Acceptance Model (TAM) with Perceived Value and Task-Technology Fit (TTF). The findings indicate that students' adoption decisions are primarily shaped by their perceptions of the tool's value, usefulness, and ability to enhance learning engagement. These results emphasize that successful integration of AI in dental education depends less on ease of use or social factors, and more on the technology's academic relevance and reliability.

Overall, the research contributes a validated and systematic framework for understanding AI adoption in professional education, combining explanatory modeling with predictive validation. It offers practical guidance for educators to integrate ChatGPT meaningfully into learning processes—by demonstrating its educational value, ensuring accuracy, and aligning its use with core learning tasks. Future studies are encouraged to assess long-term learning outcomes and explore broader cultural or institutional contexts to strengthen the generalizability of this framework.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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