The Influence of Perceived Risk and Perceived Benefit to Patient's Intention to Use AI Dental Tool (3D Oral Scanner)

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Abstract: - The use of AI technology is growing rapidly within the healthcare industry. The use of AI-based tools in dentistry is believed to improve the way dentists or dental clinics operate in this modern era, especially in orthodontic treatment as it could leverage the accuracy and the efficiency of scanning the mouth to design teeth prosthesis. However, there are several factors that may influence a patient's intention to use an AI-based tool. Therefore, understanding the customer perspective whether they accept or refuse the use of AI-based dental tools is crucial for dentists to decide investing in the right tools. This research would examine the perceived benefits and risks of AI-based tools in dentistry from real patients' perspective. The research was conducted using purposive sampling to select the participants from major dental clinics in Jakarta. Questionnaires were then given to the participants to fill and then analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) method. The results show that all variables have significant relationships with one another, with performance risk having the largest effects towards perceived risk, perceived usefulness towards perceived benefit, and perceived risk towards intention to use. This was found to be a result of direct benefits received by the patient, the characteristic of Indonesian patients that are both price-sensitive and lack of knowledge within the area, as well as the overall data collected and nature of the scanner itself. The findings provide insights to factors contributing to patient acceptance and usage towards emerging AI technologies in the field of dentistry in Indonesia.

Key-Words: - Artificial Intelligence, Perceived Risk, Perceived Benefit, Dental, AI Dental Tool, 3D Oral Scanner

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1 Introduction

Artificial Intelligence or simply known as AI is a computerized system that is programmed to have a human-like intelligence to collect and learn external data to perform various tasks [22]. This disruptive technology has transformed lives affecting how humans have instigated their basic tasks. From as simple as robots and smart assistants on smartphones such as Alexa and Siri, to those found in Netflix to provide personalized content recommendations, and even more advanced generative AI systems like ChatGPT to formulate solutions to assignments and inquiries ([20], [40], [42]).

The extent of AI implementation also spans towards businesses, where previous surveys and research shows that 90% of respondents have shown the opportunities AI offers for companies, coupled with efficient strategic decision-making skills and improvements in technologies, it emphasizes the future of rapid AI integration in upcoming years [43]. Its versatility in meeting different needs and functionalities fuels its adoption within a variety of industries, from the service industry such as hotels and airlines, to the automotive industries, and even in the healthcare industry that can bring benefit for both the business side leading to a more efficient operations with cheaper cost and from the customer side, allowing them to receive better quality goods and services ([16], [21]). A range of previous studies have shown how AI application in businesses, particularly on customer service and after-sale support, has a positive relationship towards customer experience [8].

Particularly within the healthcare industry, AI has been assisting the research and development process for new medicine, supporting clinical trials, providing patient care, and even helping doctors for diagnostics and operations [49]. In dentistry, AI development has begun to rise within the last few years, mainly acting within diagnostics, planning of treatments, predicting outcomes of treatments, and overall assisting the dentist in the decision-making process. The most popular application is for diagnosis, which is able to reduce workload while increasing the efficiency and accuracy of the diagnosis itself [10]. The 3D Oral Scanner is a digital scanner to replicate the conditions of the oral cavity in 3D format, minimizing time needed for diagnosis and the pain experienced by the patients, overall eliminating the need of manual tasks in creating dental prosthesis and increasing the accuracy of oral cavity mapping ([17], [48]). It has been tested and proven to be a reliable and valid tool to create dental prosthesis casts, reducing the possibility of errors found in traditional methods such as manual measurement plaster cast [41].

While Artificial Intelligence (AI) has a lot of benefits for dentists to perform its practice and enhance the results for the patients, there are some concerns on data security and privacy [32]. Moreover, some perspectives also show that the healthcare industry is more sensitive to new technologies where not all individuals are willing to accept the use of medical AI devices [28]. Therefore, understanding the customer perspective whether they might accept or refuse the use of AI-based dental tools is crucial in order for dentists to decide their business strategy for the future.

Recent research in the field of Artificial Intelligence (AI) in the dental industry showed that AI has the potential to be used in dentistry and at the same time there are some barriers that need to be assessed. Yet, despite the big potential and barriers AI might have to disrupt dentistry, it lacks a patient's point of view on whether they perceive AI as an advantage or a threat. Regarding these, the purpose of this research is to show a comprehensive patient’s perception on whether they intend to use dental AI-based tools, by comparing the risk and benefit in the patient’s perception.

2 Literature Review

2.1 Artificial Intelligence

The start of the interest towards modern research in the field of Artificial Intelligence (AI) started in the year 1956, this became the start for the popularization of the term with many innovations created as years go by [54]. [22] describes 3 stages of AI implementations where the first stage is known as Artificial Narrow Intelligence (ANI) where AI outperforms or equal to human ability only in one or a specific area, Artificial General Intelligence (AGI) where AI outperforms or equal to human ability in several area, and Artificial Super Intelligence (ASI) where AI outperforms human ability in all areas. Showing that AI is growing from time to time and has a wide potential to help humans perform things that are impossible for humans but at the same time might be a double-sided sword for humankind.

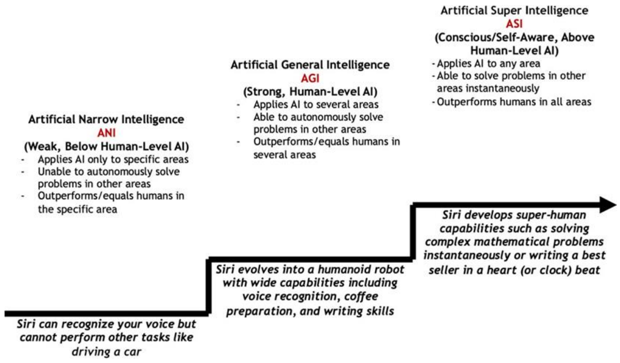

Fig. 1 Stages of Artificial Intelligence (AI) (Kaplan & Haenlein, 2019)

Specifically in the healthcare industry, AI integration has raised several concerns, hindering their acceptance or adoption. Mainly it was found that concerns are centered around data collection issues as medical information are considered to be confidential as well as ethical concerns which are related to the accountability of AI application within the sector [25]. As it is still considered to be a new type of technology, it is crucial to determine factors that influence its acceptance and uptake by the general public. The assessment on its acceptance is crucial in understanding what variables are fundamental to be considered in order to maximize its uptake [24].

2.2 3D Oral Scanner

A 3D oral scanner could also be referred to as an intraoral scanner which is a type of technology that is able to capture impressions of the dental arch through emitting certain lights and lasers and the result would be displayed on a touchscreen almost immediately in high definition quality, making it easier for dentists to obtain precise and detailed information on the oral cavity that assists in planning treatments, laboratory communications, and overall cuts time. Usually, the scanner would come with a handheld device inserted to the oral cavity to scan, a computer to process and display the information, as well as its specific software that allows the program to run smoothly. It has since then begun to replace traditional impression methods as it is a less invasive method that increases patient satisfaction and comfort during the process [6].

However, these scanners have been developed since years back, it is now integrated with AI technology that signifies a new era within prosthodontics and the overall dental industry as machine learning is now implemented to analyze data from these scans and automates the 3D files alignment. It can also be applied to help diagnosis through detecting fractures, implant placement and positions, ultimately enhancing the overall treatment diagnostics and planning process through a more accurate design of treatments [45]. An example of this would include its implementation in Invisalign where a scanner is used to create aligners which is also integrated with AI to visualize potential results after the treatment process [19]. As well as its usage in DeepCare, a company that specializes in creating AI-based diagnosis technology that also utilizes 3D scanning while using AI to track patient historical data and previous cases while also taking into consideration patient health conditions and relevant factors, such as age or financial constraints, that offers personalized and streamlined process for its patients which also supports dentists in making more informed decisions regarding patient care [9].

2.3 Intention to Use

The intention to use, or adoption intention, refers to a patient's readiness and eagerness to incorporate AI technologies into their dental care practices. This reflects the patient's openness to adopting innovative AI-driven solutions for enhancing their overall dental health experience, by comparing its risk and benefit [11]. When a patient has agreed to use an AI dental tool then we can consider it as a successful innovation of AI in dentistry, as it would be the main indicator on whether an innovation is considered as success or a failure [51].

2.4 Perceived Performance Risk

Perceived performance risk in the context of artificial intelligence in dentistry refers to the concerns users might have regarding the AI system's potential to malfunction or not perform as expected, potentially failing to deliver the desired outcomes [36]. Dentistry which is in the service industry is very well related as the service given will satisfy their needs and meet their expectation [23]. Thus, it might be a consideration for patients when choosing an AI dental tool. Thus it can be hypothesized that:

H1: Perceived Performance Risk positively influences Perceived Risk

2.5 Perceived Privacy Concern

Privacy is a significant concern for consumers when it comes to the adoption of AI in the dental industry, as the technology often requires the collection of sensitive personal information, such as medical histories, dental records, and contact details. If this information were to be compromised, it could be misused or exposed. [36]. This risk includes the possibility of service providers deliberately collecting, sharing, or selling personal data without the patient's consent, disturbing private space, as well as the risk of hackers intercepting this sensitive information, creating doubt in the patient’s mind [55]. Thus it can be hypothesized that:

H2: Perceived Privacy Concern positively influences Perceived Risk

2.6 Perceived Price Consideration

Perceived price refers to the value that patients believe they are gaining from a service of product where in this case is a dental service using the AI dental tool [7]. Price plays a critical factor that patients use to decide the use of AI dental tools, as they tend to seek maximum value from their transactions. As prices rise, patients may feel they are making greater sacrifices, leading to more consideration whether to choose AI dental tools as their option [37]. Thus it can be hypothesized that:

H3: Perceived Price Consideration positively influences Perceived Risk

2.7 Perceived Accuracy

Perceived accuracy refers to a patient's confidence in the precision and reliability of AI technology when it comes to diagnosing dental conditions [1]. This belief reflects how much trust patients place in the AI system's ability to correctly identify and assess their dental health issues, which in turn can significantly influence their overall acceptance and satisfaction with AI-driven diagnostic tools in dentistry [39]. Thus it can be hypothesized that:

H4: Perceived Accuracy positively influences Perceived Benefit

2.8 Perceived Intelligence

Perceived intelligence involves a patient's assessment of the AI system's ability to effectively and intelligently diagnose and predict dental problems [1]. It reflects the extent to which patients trust the AI's competence in analyzing their dental health and providing accurate prognosis, hence meeting patient’s demands and can influence their confidence in using AI-based tools for dental care [30]. Thus it can be hypothesized that:

H5: Perceived Intelligence positively influences Perceived Benefit

2.9 Perceived Usefulness
Perceived usefulness reflects a patient's evaluation of how valuable AI is in enhancing their understanding of their dental health. It represents the degree to which patients find AI technology beneficial in gaining insights into their dental conditions, ultimately shaping their willingness to rely on AI-driven solutions for dental care [1]. Perceived usefulness is found to have a direct impact on consumer’s behavior in terms of intention to use and adopt a technology, thus [44]. Thus it can be hypothesized that:

H6: Perceived Usefulness positively influences Perceived Benefit

2.10 Perceived Risk
Perceived Risk was introduced by Bauer in 1960 where he describes risk as the uncertainty and potential consequences linked to consumer’s action that is unfavorable. When a purchase does not meet the consumer's expectations, it can result in adverse consequences [53]. In the context of this study, perceived risk refers to the extent to which consumers recognize potential losses associated with the uncertainties of using AI in dentistry [12]. Thus it can be hypothesized that:

H7: Perceived Risk negatively influences Intention to Use AI Dental Tool

2.11 Perceived Benefit
Perceived benefits refer to the extent to which a patient believes that utilizing AI technology will enhance their dental care experience. It also involves how patients compare AI-driven innovations with traditional methods of dental services [11]. Benefits are about the added value that the patient’s received when they decided to use AI dental tools [26]. Thus it can be hypothesized that:

H8: Perceived Benefit positively influences Intention to Use AI Dental Tool

3 Research Model

Pertaining to the previous literature and hypotheses developed, the research model used within this research would be given in the figure below (Figure 2).

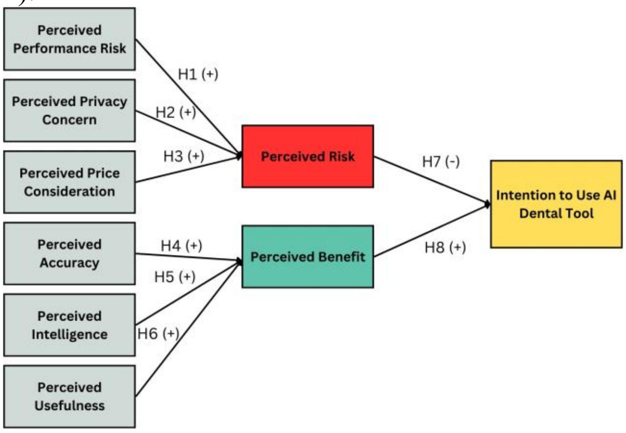

Fig. 2 Research Model

Hypothesis Developed:
H1: Perceived Performance Risk positively influences Perceived Risk
H2: Perceived Privacy Concern positively influences Perceived Risk
H3: Perceived Price Consideration positively influences Perceived Risk
H4: Perceived Accuracy positively influences Perceived Benefit
H5: Perceived Intelligence positively influences Perceived Benefit
H6: Perceived Usefulness positively influences Perceived Benefit
H7: Perceived Risk negatively influences Intention to Use AI Dental Tool
H8: Perceived Benefit positively influences Intention to Use AI Dental Tool

4 Data and Methods
This research will undertake a quantitative and cross-sectional approach to analyze the factors affecting the intention to use the AI Dental Tool from Indonesian citizens. A structured questionnaire will be administered that contains questions adapted from the variable dimensions using the Likert Scale (1 to 5). Primary data is taken using the purposive sampling method to select the participants from major dental clinics in Jakarta, with the results analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) method as there are several constructs and indicators used. Secondary data will be obtained from relevant literature and journals to support the findings from the primary data

analysis. The operationalization of the variables with its indicators used are provided in the table below.

Variables	Definition	Indicators	Scale
Perceived Performance Risk (PPR) Modified from [53]	Subjective interpretation from consumers of the possible losses that Could be experienced	The AI dental tool may have frequent malfunctions during usage	Likert 1-5
		The AI dental tool may fail to deliver results as expected	
		The performance level may be lower than its technical specifications	
		The service performance may not perform effectively as it was marketed	
Perceived Privacy Concern (PPC) Modified from [53]	Consumer perception regarding possible exposure of their private information	Privacy information could be misused, inappropriately shared, or sold	
		Personal information could be accessed by unauthorized parties without permission	
		Personal information and location could be tracked	
		Privacy could be exposed when using AI dental tool	
Perceived Price Consideration (PRC) Modified from [37]	\ Consumer perception on the price of a product based off the expected benefits obtained	Using AI dental tool could be more expensive than using traditional tool	
		AI dental tool is too high for most users	
		AI dental tool has costs that do not reflect the provided benefits	
Perceived Accuracy (PA) Modified from [1]	Customer perception on how product can accurately conduct its task function	AI dental tool can accurately obtain the teeth structure with high precision	Likert 1-5
		AI dental tool provides correct and reliable information about the oral condition	
		AI dental tool is consistent in providing accurate information of the teeth structure	
		AI dental tool can detect any teeth structure	
Perceived Intelligence (PI) Modified from [1]	Customer perception intelligenceof the technology	AI dental tool uses smart algorithms to interpret and scan teeth structures	
		AI dental tool can adjust its analysis based on different types of dental structures	
		AI dental tool can learn from previous data in detecting the teeth structure	
		AI dental tool can provide personalized recommendations based on the results of the teeth structure	
Perceived Usefulness (PU) Modified from [1]	Customer perception on usefulnessof the product or technology in improving the current situation	AI dental tool is useful to detect the teeth structure easily	
		AI dental tool increases effectiveness in making decision regarding teeth structure	
		AI dental tool makes it easy to access information about teeth structure anywhere and anytime	
		AI dental tool improves teeth health and its aesthetic by providing information about the teeth structure	
	Subjective interpretation from customers	It is probable that AI dental tool would not delivery performance that is worth its cost	

Perceived Risk (PR) Modified from [18]	on the uncertainty of the product or technology in regards of their judgement and actual performance	It is probable that AI dental tool would frustrate me due to it poor performance	
		Comparing to other technologies, AI dental tool has more uncertainties	
		It is uncertain whether AI dental tool would be as effective as my expectations	
Perceived Benefit (PB) Modified from ([29], [26], and [11])	Subjective perception of customers on how the product or technology could be beneficial for them	Using AI dental tool helps reduce time spent during scans and checkups	
		Using AI dental tool can offer me wider range of dental services	
		The quality I obtained from the AI dental tool improved my overall teeth quality	
		AI dental tool usage outweighs its initial cost	
Intention to Use (IU) Modified from [11]	The approach of customer in engaging into certain	I intent to use AI dental tool	
		I intent to use AI dental tool on my next dentist visit	

Table. 1 Operationalization Variable

4.1 Sampling and Data Collection

The population in this research are customers of dental clinics in Jakarta, and since this research will use PLS-SEM, the number of samples needed is 10 times the largest number of formative indicators. Hence, the total sample will be 200 patients from major dental clinics in Jakarta. Purposive sampling is utilized because there are criterias for the respondents to ensure the validation and relevance of data obtained, as this research aims to analyze the intention to use the 3D Oral Scanner within dental clinic practices, the sample criteria will be repetitive patients with a minimum visit of twice, male or female in the age of 20-40 years.

4.2 Data Analysis

The data analysis method will be using PLS-SEM or Partial Least Squares Structural Equation Modelling. It is a tool to conduct multivariate analysis on quantitative data which allows simultaneous analysis and measurement of variable relationships within a complex model [31]. First it will determine the reliability of the indicators as well as its internal consistency reliability, followed by convergent and discriminant validity to ensure that the questionnaire items are suitable and replicable for use. After it will analyze the inner model with assessments of the path coefficients to determine the nature and strength of the relationships, its significance values, and R squared values. Lastly, it will also conduct hypothesis testing based on the path coefficient and significant p-values to accept or reject the research hypotheses.

4.3 Results

The research collected 200 respondents to participate in the survey who fit the required criteria, it was further verified through the filtering questions ensuring that they are between 21 to 40 years old and are dental patients as they visit the dentist a minimum once every six months.

Fig. 3 Results of Filtering Questions

	Number of Respondents	Percentage
Place of Domicile		
Jakarta	193	96.5%
Tangerang	6	3%
Bekasi	1	0.5%
Knowledge of AI		
Very knowledgeable	64	32%

Knowledgeable	72	36%
Not knowledgeable	64	32%
Previous Experience with AI-based Medical Tools		
AI-Based Diagnostic Tools	60	30%
Virtual Health Tools or Smart Health Applications	119	59.5%
AI for Assisting Surgical Procedures	39	19.5%
Never experienced AI-based Medical Tools	1	0.5%
Knowledge of AI-based Dental Tools		
Very knowledgeable	44	22%
Knowledgeable	68	34%
Not knowledgeable	88	44%

Fig. 4 Results of Descriptive Questions

The descriptive questions results are given in Table 2, where it shows that the majority of the respondents reside in Jakarta, have moderate knowledge of AI, but are knowledgeable when it comes to AI-based dental tools. A large portion of the sample population are familiar with using virtual health tools or smart health applications and some have previous experience with AI-based diagnostic tools.

The outer model was then evaluated to test the reliability, where the results show that all indicators have values above 0.7 for each respective latent variable, indicating high correlation and strong accuracy in measuring each tested construct. Detailed information on the values are given in the appendix (Appendix 4). The constructed internal reliability and validity were tested where all the values were above 0.8 for the Cronbach's Alpha value and composite reliability values above 0.7, indicating excellent reliability. Furthermore, the convergent validity values (Average Variance Extracted) were all above 0.5 which means that the constructs have good convergent validity and have the ability to explain more than half of the indicator variances.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
IU	0.949	0.950	0.963	0.867
PA	0.924	0.925	0.946	0.814
PB	0.931	0.931	0.951	0.829
PI	0.948	0.949	0.963	0.865
PPC	0.924	0.926	0.946	0.815
PPR	0.910	0.910	0.937	0.788
PR	0.945	0.945	0.960	0.858
PRC	0.855	0.858	0.912	0.775
PU	0.950	0.950	0.964	0.870

Table. 2 Internal Construct Reliability and Validity

The discriminant validity were also tested using the Fornell-Larcker Criterion and HTMT values, where the values for the Fornell-Larcker criterion of each Average Variance Extracted for each construct is higher compared to correlations with other constructs, and that the Heterotrait-monotrait Ratio (HTMT) values were below 0.9. This means that each construct is distinct from one another, avoiding overlaps between ideas and increasing the accuracy of measurement.

	IU	PA	PB	PI	PPC	PPR	PR	PRC	PU
IU	0.931								
PA	0.438	0.902							
PB	0.712	0.560	0.910						
PI	0.765	0.382	0.629	0.930					
PPC	0.591	0.410	0.652	0.534	0.903				
PPR	0.689	0.400	0.649	0.632	0.670	0.888			
PR	0.823	0.453	0.707	0.711	0.691	0.813	0.926		
PRC	0.688	0.499	0.692	0.597	0.725	0.764	0.777	0.880	
PU	0.709	0.522	0.795	0.617	0.598	0.608	0.710	0.622	0.933

Table. 3 Fornell-Larcker Criterion Results

	IU	PA	PB	PI	PPC	PPR	PR	PRC	PU
IU									
PA	0.465								
PB	0.756	0.604							
PI	0.806	0.407	0.670						
PPC	0.630	0.443	0.703	0.569					

PPR	0.740	0.435	0.704	0.681	0.730				
PR	0.869	0.483	0.754	0.751	0.738	0.876			
PRC	0.762	0.563	0.775	0.663	0.816	0.864	0.863		
PU	0.746	0.556	0.845	0.649	0.637	0.654	0.749	0.690	

Table. 4 Heterotrait-monotrait Ratio (HTMT) Results

Hypothesis testing was done by path coefficient analysis supported through complete bootstrapping in order to analyze the relationships between the different constructs.

	R-squared Value
Perceived Benefit	0.687
Perceived Risk	0.729

Table. 5 R-squared Results

The R-squared value indicates that constructs for Perceived Benefit and Perceived Risk have sufficient explanatory power with 68.7% and 72.9% of variability explained respectively. For Intention to Use, Perceived Benefit and Perceived Risk can explain 71.1% of variability in the construct, showing good explanatory power.

Hypothesis	**Path**	**β (Beta)**	**t-value**	**p-value**	**Description**	**Result**
H1 (+)	PPR → PR	0.484	4.940	0.000	Positive, significant	Supported
H2 (+)	PPC → PR	0.151	2.558	0.011	Positive, significant	Supported
H3 (+)	PRC → PR	0.298	3.251	0.001	Positive, significant	Supported
H4 (+)	PA → PB	0.183	3.231	0.001	Positive, significant	Supported
H5 (+)	PI → PB	0.207	4.069	0.000	Positive, significant	Supported
H6 (+)	PU → PB	0.572	9.104	0.000	Positive, significant	Supported
H7 (-)	PR → IU	0.640	7.716	0.000	Positive, significant	Not Supported
H8 (+)	PB → IU	0.259	3.479	0.001	Positive, significant	Supported

Table. 6 Hypothesis Testing Results

From the path coefficient analysis conducted, it can be concluded that all the proposed hypotheses were supported with the exception of Perceived Risk towards Intention to Use (H7), as the hypothesis suggested a negative relationship but instead the β value was positive. All relationships were positive indicated by the β value and significant indicated by the p-value that were below 0.05 and the t-value above 1.96 for significance at 95% confidence level. For Perceived Risk (PR), Perceived Performance Risk has the largest effect (β value of 0.484), followed by Perceived Price Consideration (β value of 0.298), and lastly Perceived Privacy Concern (β value of 0.151). While for Perceived Benefit, the largest effects were by Perceived Usefulness (β value of 0.572), then Perceived Intelligence (β value of 0.207), and lastly Perceived Intelligence (β value of 0.207). For Intention to Use, Perceived Risk has stronger effects (β value of 0.640) compared to Perceived Benefit (β value of 0.259).

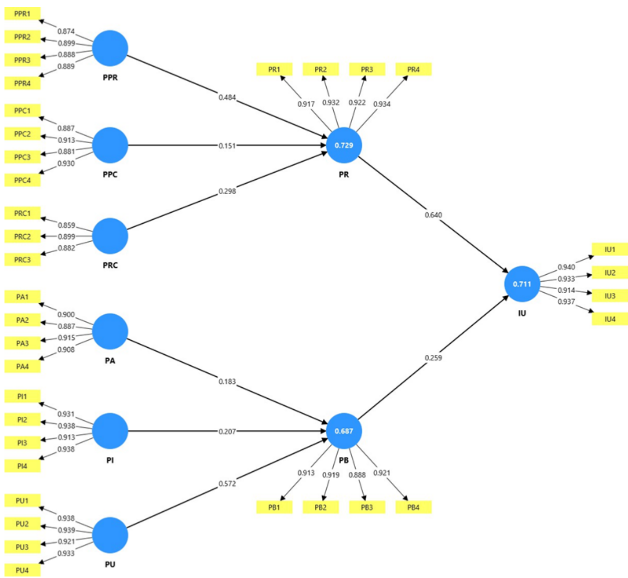

Fig. 5 Inner and Outer Model

5 Discussion

The results show that seven from the eight hypotheses were supported, with the exception of Perceived Risk having positive effects towards Intention to Use, however this might be caused by the negative statements that are interpreted by SmartPLS as positive correlations, thus contributing to the hypothesis rejection. Subsequently, it might also be said that there is significant correlation towards Perceived Risk where increased risk perception would negatively impact intention to us.

Perceived Performance Risk (PPR) was confirmed to have a positive and significant effect (β value of 0.484) towards Perceived Risk. This is in line with previous findings where it was found that performance risk may influence risk and behavior, particularly in the study the performance risk of a hotel service would result in switching to a different provider [50]. Although the industrial context is different it shows how performance risks amplifies overall perceived risk towards customers, and might impact the patient's intention to use. Its effects were the highest amongst the other indicators of Perceived Risk. This is because when referring to technology, consumers often prioritize functionality and reliability that underscores their overall consideration for usage ([33], [56]). Especially in healthcare settings, these products or technologies physically interact with the patient body where risks of failure in performing might impact the satisfaction and trust of the patient [23]. As the patient may have no experience with the tool beforehand, it gives rise to certain skepticism on the actual specifications that are advertised, unable to meet their expectations.

Perceived Privacy Concern (PPC) was the least influential factor towards Perceived Risk with positive and significant effects (β value of 0.151). This was supported by previous findings of [15] that found the same relationship resulted in intention to use e-commerce platforms. [2] also highlighted the same points by which perceived privacy concerns had effects on Internet of Things (IoT) usage and trust in healthcare through mediation of perceived risk. This is because personal data in the context of healthcare is particularly more sensitive, due to certain factors of confidentiality, availability, integrity, and non-repudiation that healthcare settings should pay attention towards [52]. However the context of the 3D Oral Scanner that detects mouth structures might not be as concerning as performance risk as it could not directly identify the patient identity. Risks related to privacy are often focused on potential problems when the data is disclosed and the opportunistic behavior of the data owner once they have access to this personal information [27]. Given that the oral cavity would be perceived to have less benefits for the data owner to exploit, thus it would not contribute as much to risk perceptions.

Perceived Price Consideration (PRC) had the second largest effects (β value of 0.298) towards Perceived Risk, with the relationship being positive and significant as similarly found in previous studies such as that conducted by [53]. This might be because of the fact that price becomes an indicator of product quality and overall value through mediation of perceived risk [38]. Additionally, price considerations are also developed with past purchases and experience, influencing their own judgement of justice given based on the price point [7]. Dental clinics especially when using high-tech tools and products are often not covered by insurance payments and this amplifies the cost-benefit trade-off in customer minds where perceived risk is amplified, especially in the context of developing countries where financial considerations play a significant role in influencing customer behavior.

Perceived Accuracy (PA) has the lowest effects (β value of 0.207) towards Perceived Benefit although the relationship was significant and positive. This was in line with findings by [5] where accuracy influences the overall quality in health-related technologies, by which this is perceived as some sort of benefit by the patient. Its low effects could be attributed to the lack of knowledge of the patients in understanding technical data, making it an intangible aspect that could not be directly observed. It is an abstract concept which could be explained through other factors such as usefulness or saved time and cost.

Perceived Intelligence (PI) has significant, positive effects (β value of 0.207) towards Perceived Benefit with it being the second largest determinant. This is supported by findings highlighted by [35] where it showed that the particular intelligence behind technologies such as algorithms or data analysis capabilities are perceived to be beneficial in terms of improved decision making. However, similarly to Perceived Accuracy, this aspect is often overlooked due to its intangible nature. Its higher effects might be due to the product being powered by Artificial Intelligence, which in itself already emphasizes the difference from traditional methods, namely improved intelligence of the computer or technology.

Perceived Usefulness (PU) was the most influential factor towards Perceived Benefit with positive and significant effects (β value of 0.572). This was supported through previous findings by [13] where it showed that in the context of a developing country, perceived usefulness fully mediates the effect between smart technology application in healthcare towards its intention to use. This is because perceived usefulness is also associated with ease-of-use, which makes the patient perceive it as not only functionally beneficial but also its usage is considered to be simple and easy [3]. Also, the overall usefulness would translate to observable changes the patients can easily understand, given that accuracy and intelligence would mostly be felt by the dental practitioners operating the technology on the patients.

Perceived Risk (PR) was found to be the larger influence towards Intention to Use with the relationship being positive and significant (β value of 0.640). Previous study by [46] also found similar implications with perceived risk having significant correlations towards intention to use electronic based health consultation services. Through the risk-aversion model that is centered around health-related decisions, risks of utilizing the treatment or new technology would outweigh the benefits, translating to patients to avoid loss rather than trying to obtain the said benefits of the treatment [34]. The perception of risk would be seen as deal-breakers while benefits are perceived as an added-on bonus when considering trying the treatment, as the lack of knowledge and familiarity towards the technology would amplify risk perceptions. Furthermore, as the 3D scanner is a type of technology that is a form of improvement from the previous method in terms of accuracy and time, the switching cost in terms of price and performance would have significant influences because the benefits are not seen as detrimental to their life expectancy or more dire outcomes.

Perceived Benefit (PB) had a weaker effect (β value of 0.259) compared to Perceived Risk but still had a significant, positive relationship with Intention to Use. This is aligned with findings by [14] where perceived benefit has a positive effect for patients to use online health consultation services as it is concerned with how a patient perceives their future state to be improved after the usage of the technology. Through this factor, patients who see and believe in the value obtained from the technology would have increased likelihood of adoption. This is because outlined in the Technology Acceptance Model, cost-benefit analysis is crucial in determining behavior towards new technology, given that it is mostly influenced by compatibility, benefit, and complexity, the perception of benefit is stronger as patients do not physically need to understand on how to use the scanner itself [4]. The patient would also have better experience in using the technology, which not only gives intrinsic benefits but also saves cost and time, a key determinant in overall acceptance of the 3D Scanner.

The overall respondent profile would also support the findings and discussions in this research. As the majority reside in the Jakarta area, as well as the clinics operating in the same area, previous findings show that these people are more focused on finding the best value that could be given to them as well as their characteristic of being more price-sensitive [47]. This would translate to them having larger considerations for price and value, given that their previous experiences were from virtual health tools. Lastly, their knowledge towards AI-based dental tools are still relatively low, which may contribute to the lack of significance and effects of perceived intelligence and privacy concerns towards their respective latent variables. Thus the lack of general knowledge on deeper attributes of AI technology may result in them placing less importance on these factors within their decision-making process.

6 Conclusion

The 3D Oral Scanner is an excellent example of AI implementation within the dental industry that is able to streamline and increase the efficiency of more complex treatments and procedures to its patients. Through questionnaires given to dental patients within the Jakarta area, the research found that both perceived risk and benefit have significant influence towards their overall intention to use. However, intention was mainly affected by risk rather than benefit, this is mainly due to the risk aversion found in the Indonesian population that prioritizes avoiding losses specifically in decisions regarding their health or medical services. This research found that this risk was mainly influenced by utmostly performance, price, and lastly privacy. Consequently, benefit was found to be secondary in effect strength where factors such as usefulness, intelligence, and accuracy, still were valued by the customer to some degree. The demographics of the respondent also supported the findings, where the characteristics of the population is centered around product value and cost-benefit trade-offs. The limited knowledge of the participants might contribute to the lack of significance towards intangible factors. This research sheds light on critical insights that gives clarity on how different factors influence patients adoption towards AI-based dental tools, by which it is mainly mediated by risk and through that performance-related concerns.

7 Limitation and Recommendation

The limitations found in this research was the limited sample size that could not encompass the entire population of dental patients in Indonesia, additionally their limited knowledge may introduce certain bias in the results based on their familiarity and previous experiences. Further recommendations that could be done for future research is to conduct it with a larger sample size to gain better generalization of the population, as well as to include other variables that make up perceived risk, benefit, and intention to use as the R squared values are still moderate (60-80%), indicating that there are still more influential factors that affects the constructs. Also studying dental patients across various geographical areas would also provide more comprehensive insights that could be generalized from the Indonesian population. While for dental clinics, it could be obtained from the research that it should focus on lowering perceived risks as it is the bigger determinant for intention to use.

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