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Integrating Cognitive and Emotional Factors for AI Chatbot Use in Healthcare Sector

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ABSTRACT

This research integrates Cognitive and emotional aspects to understand the intention to continue using AI chatbots in the health sector. The rational/cognitive aspects are represented by perceived usefulness, while the emotional aspect is represented by perceived coolness. Valid questionnaires were collected from 240 respondents, with purposive sampling as the chosen sampling method. The research model was tested using SEM-PLS. The results indicate that perceived usefulness has significant effects on satisfaction and continuance intention to use the AI Chatbot. Perceived coolness, representing the emotional factor, also has a significant effect on satisfaction and intention to continue. The emotional factor was found to have a stronger effect than rational factors in determining the AI Chatbot continuance in healthcare services in Indonesia. Managers, healthcare service providers, and AI designers must highlight the enhancement of both rational and emotional aspects to gain satisfaction from health service users. Satisfaction is proven to be important for continuing intention for AI chatbot use in healthcare services. This study contributes to theoretical research by combining the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM) within the context of healthcare services. Also, a unique aspect of this study is the integration of both rational and emotional aspects within the TAM framework.

Keywords: Health-care; perceived-coolness, perceived-usefulness, customer-satisfaction; continuous-intention.

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INTRODUCTION

Artificial intelligence (AI) is experiencing increasing societal acceptance and widespread adoption due to its capability to facilitate efficiency, accelerate work processes, and support decision-making. AI has been extensively utilized across a diverse range of sectors, including commercial business, industrial technology, automotive, healthcare, finance, customer service, and numerous other sectors (Buhalis & Moldavska 2022; Esmaeilzadeh 2025). Despite the global acceptance of AI applications, the response to their utilization remains highly diverse. Consumer responses and behaviors regarding AI adoption exhibit significant variance. Studies by Cheng and Jiang (2020) found that AI chatbots are able to positively influence user satisfaction and foster sustained loyalty. The prolonged waiting times in

manual services has been found to be the reason respondents choose AI chatbots over human customer service. Despite many challenges and limitations, the mass adoption of AI chatbots around us remains widely acknowledged.

In the healthcare sector, studies similarly predict that AI will play a critical role in shaping the future of global health services (Schwalbe & Wahl 2020). The experience of the pandemic has significantly necessitated the use of digital technologies, leading to the growing popularity of telemedicine, including the deployment of AI chatbots. Despite the rapid advancement of AI technology, professional healthcare services cannot be managed solely through data quality without also considering the emotional state of healthcare consumers. The varying nature of diverse environments and distinct patient conditions renders both cognitive and affective considerations equally important. Ladhari et al. (2017) underscore the pivotal role of positive user emotions in enhancing satisfaction and loyalty toward an AI chatbot. They also identified that emotional aspects, specifically delight and enthusiasm, can significantly boost the intention for continued AI chatbot use. Conversely, negative emotional responses tend to disrupt the sustained consumer interaction with the AI chatbot. Research by Kim (2024) further supports the finding that negative emotions impact dissatisfaction, which may ultimately lead to a decision to discontinue use.

The adoption of AI chatbots is still relatively nascent in supporting healthcare services. Public acceptance remains highly diverse and often limited to educated populations or those residing in major urban areas with more pervasive internet infrastructure. Based on prior literature, Jenneboer et al. (2022) identified customer satisfaction as the most frequently researched topic for analyzing factors that influence customer loyalty toward chatbots. This study addresses previous research gaps, which mainly consider the rational/cognitive factors in the model for predicting behaviors towards AI chatbots. Conventional research in the technology adoption models is still predominantly focused on rational aspects and inadequately accommodates the emotional dimension, which is important for service sectors such as the healthcare industry (Li et al. 2024). This study, therefore, builds a model that integrates both user cognitive and emotional dimensions in predicting the behavioral intention to continue using AI chatbots. Specifically, this research combines the Technology Acceptance Model (TAM) (Davis 1985, 1989) and the Expectation-Confirmation Model (ECM) as the theoretical basis for the research model developed. The cognitive aspect is built by perceived usefulness, and the emotional aspect is represented by perceived coolness. Previous research by Li et al. (2024) supports the role of positive emotions in the sustained use of AI chatbots. These two dimensions (perceived usefulness and perceived coolness) will be analyzed for their influence on satisfaction, thereby providing a comprehensive framework for the intention to continue using AI chatbots in healthcare services. This study offers three main contributions: 1) An integrated framework to understand the factors influencing the intention for continued AI chatbot use by integrating cognitive aspects (perceived usefulness) and the affective aspect (perceived coolness). 2) extending the conventional TAM model by integrating with ECM, thus building a more comprehensive model explaining satisfaction in AI chatbot continued use. 3) Providing valuable insight for AI chatbot use in healthcare sectors, therefore better facilitating decision-making and enhancing healthcare services.

LITERATURE REVIEW

AI Chatbot and Indonesian Healthcare

The Indonesian government has designated healthcare as a priority area for national AI development, aligning with the country's accelerated digital transformation strategy and Artificial Intelligence roadmap. Through the Ministry of Health's “Satu Sehat” mobile application, various health data, including medical records, vaccination history, and laboratory results, are being integrated into a single platform to drive efficiency and facilitate public access to health information (Mediakom 2024). Acceptance of AI chatbots in Indonesia is generally positive, despite encountering several technical and social challenges. Health chatbots have been adopted by both hospitals and specific health applications,

such as Halodoc and BPJS Kesehatan (CHIKA). The level of acceptance is influenced by factors including information quality, accuracy, ease of access, emotional experience, and the practicality these tools offer in supporting healthcare delivery (Jawahir et al. 2022). Research by Widhyana (2025) on users of the BPJS Kesehatan chatbot (CHIKA) demonstrated reasonably high acceptance and public trust, although instances of unresponsive chatbots were still observed.

The Technology Adoption Model (TAM)

The Technology Acceptance Model (TAM) is frequently utilized as the primary foundation in technology management and behavioral studies to explain user acceptance, focusing on the analysis of perceived usefulness, perceived ease of use, attitude, and behavioral intention (Davis, 1989). TAM is widely recognized as one of the most effective frameworks for explaining user reactions to technological innovations (Kung et. al. 2023). Since its introduction by Davis around 1989, TAM has been adopted as a robust theory to explain the acceptance of new technology across various fields, and more recently, has been applied as a model for AI acceptance, including AI chatbots (Ashfaq et al., 2020). In this research, TAM was selected as the core theoretical framework to explain user acceptance of AI chatbots in the Indonesian healthcare sector. The healthcare field, which is also beginning to adopt AI in its services, faces challenges regarding user acceptance of AI chatbots. Currently, research on user responses to AI chatbots for healthcare services in Indonesia remains very limited. By extending the TAM model, this study further integrates both rational and emotional aspects to enhance the understanding of user satisfaction, which is subsequently expected to influence the intention for continued use of AI chatbots.

The Expectation-Confirmation Model (ECM)

The Expectation-Confirmation Model (ECM) is a theoretical framework that explains a user's intention to continue using a service, focusing on the user's experience after initial usage of that service (Obeid et al. 2024; Al Amin et al. 2024). This differs from the Technology Acceptance Model (TAM), which primarily emphasizes analysis during the initial adoption phase of new technology. In the present study, ECM was selected as the theoretical framework to explain users' satisfaction and intention for sustained use of AI chatbots in healthcare services. ECM was first proposed by Bhattacherjee (2001) and has since been widely applied to predict consumer behavior in the business domain. Three key variables, *"perceived usefulness, perceived coolness, and satisfaction,"* were utilized to predict the intention for continued AI chatbot use in this study.

HYPOTHESES DEVELOPMENT

Perceived Usefulness and Satisfaction

Perceived usefulness (PU), as one of the core variables in the Technology Acceptance Model (TAM), refers to how users perceive the benefits gained while utilizing a new technology (Bhattacherjee 2001; Huang & Liu 2024). The successful development of new technology, including service systems with AI chatbots, is significantly influenced by users' perception of the obtained benefits and, subsequently, their satisfaction after use. Previous research has demonstrated that building a positive perception of user satisfaction is achieved through perceived usefulness, easily comprehensible information, and seamless interaction (Chung et al. 2020). Chung et al. (2020) asserted that when users find an AI chatbot to be effective, beneficial, facilitating information retrieval, and convenient to use, their satisfaction increases. Several previous studies, including those by Nguyen et al. (2021), Joshi (2025), and Eren (2021), have explored the influence of perceived usefulness on AI chatbot usage satisfaction. Nguyen et al. (2021) confirmed that the AI chatbot's ability to meet user expectations is likely to generate satisfaction and promote the continued adoption of the tool. Similarly, Eren (2021) demonstrated that the AI chatbot's

capability to fulfill user expectations positively impacts satisfaction during use (Joshi 2025). Therefore, we hypothesize that:

H1. *Perceived usefulness has a positive effect on AI chatbot user satisfaction.*

Perceived Coolness and Satisfaction

The sustained adoption of technology is not solely determined by users' cognitive factors but also by the feelings of pleasure and comfort experienced during its use. In the context of technology adoption, Davis et al. (1985) defined perceived coolness as the extent of pleasure or fun derived from using the technology. This perceived coolness serves as an intrinsic motivation arising from a user's positive affective experience, which can significantly influence technology adoption behavior (Teo & Noyes 2011). Perceived coolness is realized when individuals gain experiences that yield pleasure and delight (Holbrook & Hirschman 1982). Specifically, when users exicited in utilizing an AI chatbot, they are motivated to continue interacting with it (Kim et al. 2025b). McLean et al. (2020) found that positive emotions arising during interaction with technology can affect the overall evaluation process, which in turn influences user satisfaction, including the use of AI chatbots (Rouibah et al. 2021). Regarding consumer interaction with AI chatbots, an enjoyable and entertaining interaction is likely to trigger positive emotions (Chung et al. 2020), subsequently influencing overall satisfaction (Park 2020). Therefore, this leads us to propose the following hypothesis:

H2: *Perceived coolness has a positive effect on AI chatbot user satisfaction*

Satisfaction and Intention to Continue

Intention for continued use can be defined as a user's willingness to sustain the use of a technology over a specific period (Huang & Zou 2024). Nguyen et al. (2021) clarified that when a chatbot service meets user expectations and satisfaction, this positively influences the intention for long-term sustained use. Similarly, Eren (2021) identified that an AI chatbot service capable of fulfilling customer expectations will have a significant positive impact on satisfaction. Hsu and Lin (2023) argued that emotions can have a significant impact on the decision-making process, including forming evaluations and choosing actions. The satisfaction derived from using an AI chatbot service generates positive emotions, which subsequently foster a more positive attitude and inclination toward the new technology (Kim et al. 2025a). As previously explained, research by Bhatnagr and Rajesh (2024) demonstrated that satisfaction with the use of a digital platform determines the intention for sustained usage. Based on the above principles, our research proposes the following hypothesis:

H3: *Satisfaction has a positive effect on intention to continuously use AI chatbot.*

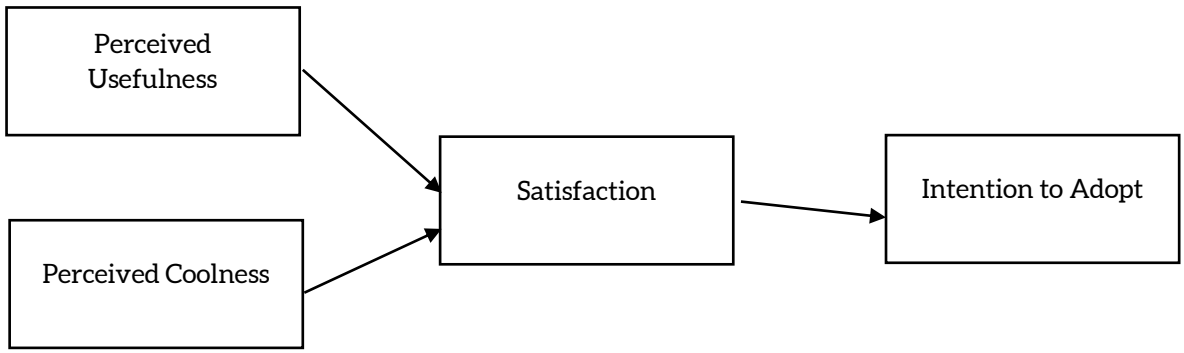


Figure 1. Research Model

METHOD

Survey Instruments

This research employs a quantitative approach involving the development of a structured questionnaire. There are four key variables derived from previous studies. The corresponding questionnaire was meticulously adapted to fit the specific context of AI chatbot application use in healthcare. To measure Perceived Usefulness, three items were developed based on the work of Kim et al. (2025b) and Zhao et al. (2024). Perceived Coolness, consisting of four items, was drawn from the study by Li et al. (2024). The variables for Satisfaction (four items) were developed from Niu and Mvondo (2024) and Kim et al. (2025a). Finally, six items to measure Intention for Continued AI Chatbot use were adopted and developed from the research of Niu and Mvondo (2024). All statements within the instrument were evaluated using a six-point Likert scale, with options ranging from 1, representing *"strongly disagree,"* to 6, representing *"strongly agree"*.

Sample and Data Collection

The participants recruited for this study primarily consisted of urban residents, specifically encompassing university students and professionals employed across Indonesia's major cities. A purposive sampling methodology was implemented to collect the necessary data, allowing the research to focus exclusively on a target group that satisfied two essential criteria: first, having prior experience utilizing an AI chatbot for healthcare-related services, and second, possessing demonstrated knowledge regarding various AI chatbot applications. This study successfully collected 540 valid questionnaires. With this final sample size of 540, the data were then subjected to further analysis. Table 1 presents a summary of the demographic profile of the respondents. The gender distribution comprised 53.1% male and 46.9% female. Regarding age, the majority of respondents belonged to the millennials (77.8%), followed by the Z generation (21.5). Concerning employment status, 61% reported work in the private sector, 27.6% students, and the rest worked in government or were self-employed.

Table 1. Respondents' Profile

Inclusion Criteria	Classification	Sum	Percent
Gender	Man	287	53.3
	Woman	112	46.7
Age Cohort	15 – 19 years old	52	22
	20 – 29 years old	187	78
	30 – 39 years old	1	0
	Above 40 Years	0	0
Education	Secondary school	66	27.5
	Bachelor	147	61.3
	Master	19	7.9
	Other	8	3.3
Expense	Less than IDR 3,000,000	126	52.48
Monthly	IDR 3,000,000 — IDR 6,000,000	80	33.3
	Above IDR 6,000,000	34	14.22
Profesion	Student	142	59.2
	Private Sector	21	8.7
	Government Employees	44	18.3
	Self employed	33	13.8

Sources: Data Processing Results SPSS 2025

Statistical Analysis

SEM-PLS was utilized following a two-step procedure. First, the measurement model was evaluated to confirm the validity and reliability of the constructs. Second, the structural model was analyzed to assess the hypothesized relationships of influence. The first step in the main analysis involved assessing the reliability and validity of the constructs. To examine internal consistency reliability, the results of Cronbach's Alpha and Composite Reliability were evaluated. Convergent validity was assessed using the values of Average Variance Extracted and factor loadings. Finally, discriminant validity was examined using two established criteria: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

RESULTS

Measurement Model Assessment

As detailed in Table 2, the results demonstrate that every construct meets or exceeds the established benchmarks, indicating their internal consistency and validity. Specifically, the Cronbach's Alpha scores for all constructs range from 0.791 to 0.910. Nunnally & Bernstein, (1994) suggested that the variable should pass the threshold of 0.7 to be considered acceptable. The Composite Reliability figures range between 0.864 and 0.936, exceeding the 0.7 benchmark proposed by Fornell and Larcker (1981) and further supporting the reliability of the constructs. Furthermore, the factor loadings for each observed item were recorded above the 0.7 threshold, except perceived coolness, where we recorded a 0.616 loading factor. The Average Variance Extracted (AVE) values for all constructs were recorded between 0.616 and 0.784, significantly exceeding the minimum requirement of 0.5 recommended by Fornell and Larcker (1981). This evidence confirms adequate convergent validity, suggesting that each construct effectively accounts for a majority of the variance within its respective indicators.

Table 2. The Results of The Measurement Model

	Indicator	Factor Loading	VIF	Cronbach's Alpha	CR	AVE
Satisfaction (Niu & Mvondo, 2024; Kim et al., 2025a)				0.908	0.936	0.784
	Your perception of using an AI health Chatbot:					
S1	I am satisfied with my decision to use AI Chatbot.	0,875	2,776			
S2	I am satisfied with my experience using AI Chatbot.	0,888	2,898			
S3	My choice to use AI Chatbot was a good one.	0,896	2,867			
S4	Utilising AI Chatbot brought my expectations close to a satisfactory.	0,882	2,723			
Perceived Usefulness (Kim et al.,2025b; Zhao et al., 2024)				0.820	0.893	0.736
	Your perception of using an AI health Chatbot:					
PU1	Using AI Chatbot allows me to gather information faster.	0,879	2,348			
PU2	Using AI Chatbot increases my productivity.	0,813	1,483			
PU3	Using AI Chatbot saves me time.	0,880	2,443			
Perceived Coolness (Li et al., 2024; Niu & Mvondo 2024)				0.791	0.864	0.616
	Your perception of using an AI health Chatbot:					
PC1	AI Chatbot is a cool product.	0,825	1,726			
PC2	Using AI Chatbot feels cool.	0,680	1,360			
PC3	Just like Chat GPT, AI Chatbot has a variety of cool features.	0,804	1,630			
PC4	The use of AI Chatbot to support services will become increasingly popular.	0,821	1,740			

Indicator		Factor Loading	VIF	Cronbach's Alpha	CR	AVE
Intention to continue (Niu & Mvondo 2024)				0.910	0.933	0.910
	Your perception of using an AI health Chatbot:					
IC1	I plan to continue using AI Chatbot in the future.	0,821	2,233			
IC2	I will continue to use AI Chatbot regularly, as I do now.	0,871	2,856			
IC3	I plan to increase my use of AI Chatbot in the future.	0,876	2,846			
IC4	I am happy to share positive things about using AI Chatbot with others.	0,879	2,399			
IC5	I am happy to recommend that others use AI Chatbot.	0,842	2,062			

According to the Fornell-Larcker criterion, the square root of the Average Variance Extracted (AVE) value for each construct must be higher than the construct's correlation with all other latent variables. The research findings demonstrated that the square root of the AVE value for each construct was higher. Specifically, discriminant validity is confirmed when the squared value of the AVE, which lies on the main diagonal of the correlation matrix, is higher than the inter-construct correlations. Additionally, discriminant validity must be tested using the HTMT ratio, where a value below 0.9 (Henseler et al. 2015) or, more stringently, below 0.85 (Hair et al. 2019) is required for the construct to be declared valid. Based on Table 3. these results provide empirical support for the discriminant validity of the measurement model, confirming that the constructs are internally coherent and well-founded theoretically.

Table 3. Discriminant Validity

Fornell-Larcker				
	AI Continue Use	**Perceived Coolness**	**Perceived Usefulness**	**Satisfaction**
AI Continue Use	0,858			
Perceived Coolness	0,677	0,785		
Perceived Usefulness	0,683	0,679	0,858	
Satisfaction	0,640	0,737	0,631	0,885
HTMT				
AI Continue Use				
Perceived Coolness	0,797			
Perceived Usefulness	0,786	0,832		
Satisfaction	0,698	0,860	0,725	

Table 4. Summary of Hypothesis Testing

Structural Path	**H**	**PC**	**Bootsrapping**		**R2**	**F2**	**Q2**	**Result**
			P Value	**T Statistics**				
		Satisfaction			0.575		0.442	
PC → S	H2	0,573	0,000	9,174		0.417		Supported
PU → S	H1	0,242	0,000	4,021		0.074		Supported
		AI Continue Intention			0.409			
S → IC	H3	0,640	0,000	13,011		0.692	0.295	Supported

Notes: *H= Hypotheses; PC Path Coefficients; S=Satisfaction; PC=Perceived Coolness; PU=Perceived Usefulness; IC=Intention to Continue.*

Structural Model Assessment

Prior to analyzing the structural relationships, it was essential to conduct a collinearity analysis to ensure that the regression estimates were unbiased. According to Hair et al. (2019), the Variance Inflation Factor (VIF) values should ideally be lower than 3. The PLS analysis results confirmed the absence of collinearity issues, as all VIF values were found to be below the threshold of 3 (see Table 2). Following the VIF test, the structural model quality was evaluated by examining three key metrics: 1) the coefficient of determination (R2), 2) the effect size (f2), and 3) the validated cross-redundancy (Q2).

First step. The R2 value indicates how well the independent variables collectively explain the variance in the dependent variables. The predictive power categories based on the R2 value are defined by the following criteria (Hair et al., 2019; Hair et al. 2022): R2 < 0.25 is weak, R2 ≤ 0.25 and < 0.50 is moderate, and R2 > 0.50 is substantial. The results indicate a moderate and substantial explanatory power of the exogenous variables on the endogenous variables, as both R2 values fall within the moderate category (≤ 0.25 and < 0.5) and substantial category >0.5 (Table 4).

Second step. In evaluating the f2 value, Hair et al. (2022) categorize f2 as small (0.02-0.15), medium (0.15-0.35), and large (>0.35). This study found small sizes for the perceived usefulness on satisfaction (0.074). Effect size for (perceived coolness to satisfaction) and satisfaction to intention to continue are considered large.

Third step. The analysis for Q2 step in model evaluation involved observing the predictive relevance (Q2), which tests the model's predictive power using Stone-Geisser's Q2 (Hair et al. 2019). Predictive relevance is observed d exclusively for the endogenous variables. As shown in Table 4, all Q2 values are above zero, indicating that the constructed model possesses acceptable predictive power. The results of the one-tailed hypothesis test are also presented in Table 4, where the underlying assumption for hypothesis development is recommended.

Hypotheses Testing Results

The results of the hypothesis testing, which are presented in Table 4 and Figure 2, reveal that three of the proposed relationships are statistically significant and positive, thereby providing empirical support for the conceptual model. The specific influence of these relationships was assessed by examining the path coefficient (β), the level of significance (p-value), and the T-statistic (t-values). Perceived usefulness was identified as having a significant positive effect on satisfaction (12: $\beta = 0.242$, $p < 0.00$). This suggests that perceived usefulness factors, such as the speed of information acquisition and time savings, positively influence user satisfaction with the AI chatbot, particularly within the sensitive healthcare context. The path coefficient from perceived coolness to satisfaction (H3: $\beta = 0.573$, $p < 0.00$) indicated a statistically significant positive relationship and the magnitude of this effect is relatively moderates-strong. This is interpreted to mean that although the comfort and coolness derived from operating the AI chatbot influence user satisfaction, its contribution is comparatively minor in the context of health services. Finally, satisfaction was observed to significantly and positively influence intention to continue use (H7: $\beta = 0.640$, $p < 0.00$). This outcome suggests that an AI chatbot that successfully cultivates satisfaction (offering a positive experience and fulfilling expectations) will positively drive users' positive behavioral intention to continue using the AI catbot services.

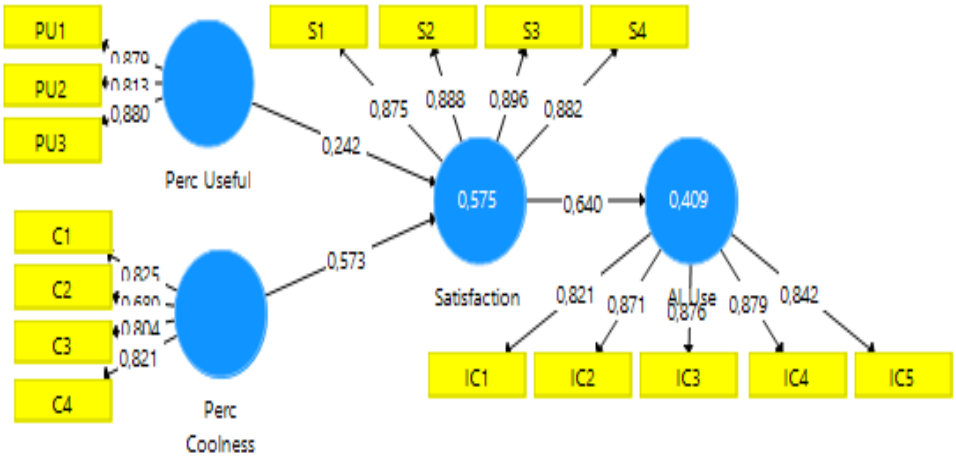


Figure 2. Path Coefficients of The Structural Model

Discussion

To understand satisfaction and the continuance intention regarding AI chatbot usage, this research integrates the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM). The ECM is specifically employed to understand continuance intention, as it focuses on the post-adoption experience of AI chatbots (Obbeid et al. 2024, Al Amin et al. 2024), examining how users process their experiences and decide whether to continue usage (Huang & Liu 2024). Meanwhile, the TAM (Davis 1989) is used to understand how consumers decide on usage in the initial adoption stage of the AI chatbot. The novelty of this study is the combination of rational and emotional factors by incorporating perceived usefulness and perceived coolness into the traditional TAM model. The findings of this study are consistent with the hypothesized relationships developed and are also supported by previous studies (e.g., Bravo et al. 2021; Choe et al. 2021; Li et al. 2024). Similar findings are also found for perceived coolness in influencing satisfaction, and continuance intention (Huang & Liu 2024, Li et al. 2024, Ashfag et al. 2020; Joshi 2025).

From a rational perspective, perceived usefulness was found to positively influence satisfaction. This implies that the perception that the AI chatbot offers clear usefulness plays a crucial role in shaping users' satisfaction with AI chatbots in the healthcare sector. This finding aligns with prior research conducted by Liu et al. (2024), Huang & Liu (2024), Niu & Mvondo (2024), and Joshi (2025) regarding the role of perceived usefulness in influencing satisfaction and continuance intention. From a rational aspect, this study provides empirical support for the importance of perceived usefulness variables in determining the intention of AI chatbot users in the healthcare sector.

From an emotional perspective, our study indicates that perceived coolness significantly influences satisfaction in the use of AI chatbots within the healthcare sector. Interestingly, perceived coolness demonstrated a strong influence, as evidenced by the high path coefficient, and similarly, the effect size was also strong in its contribution to user satisfaction. In the health care sector, this study proves the high emotional factor, considering the life risk and the high cost of the health services in Indonesia. This suggests that the emotional variable is highly important to consider when understanding users' reasons for continuing the use of AI chatbots in healthcare services. This finding is consistent with prior research showing that perceived coolness influences the intention to adopt/continue the use of new technology in the context of AI chatbot users (Huang & Liu 2024; Niu & Mvondo 2025; Li et al. 2024), and particularly the study by Ashfaq et al. (2024) in the healthcare domain.

Regarding the mediating effects, our research supports that satisfaction serves as a mediating variable between perceived usefulness, perceived coolness and on intention to continue use. Consistent with TAM and ECM theories, during the initial adoption stage of a new technology (TAM) and the post-usage experience stage, satisfaction hold critical role in the decision to continue using the AI chatbot.

Previous studies have also identified the crucial roles of satisfaction, including Mostafa and Kasamani (2022), Montazemi & Qahri-Saremi (2015), Chung et al. (2020), and Joshi (2025). These studies emphasize that due to the inherent high-risk nature of online interactions, satisfaction is necessary component when exploring the intention to adopt and continue using technology. Particularly within the healthcare sector, where the risks are substantial for the users, underscoring the vital consideration of satisfaction in this research model.

In Indonesia, through the Ministry of Health's "Satu Sehat" mobile application program, the optimization of healthcare services via AI Chatbots is expected to be realized soon. This optimization is intended to support medical professionals, enhance services, and expand access to health information. Research on AI usage behavior is crucial for improving the quality of healthcare services. A comprehensive research model that integrates both rational and emotional aspects is expected to further facilitate the public's acceptance of AI chatbot technology.

Theoretical Implications

This research offers several theoretical contributions in the context of AI Chatbot adoption and, specifically, user behavior. Firstly, this study combines the Technology Acceptance Model (TAM) for understanding technology acceptance and the Expectation-Confirmation Model (ECM) for understanding continuance intention. Our research model also integrates both rational and emotional aspects to comprehensively capture the reasons behind AI chatbot usage, whereas previous studies, utilizing TAM or UTAUT models, mainly considered only rational factors. This study extends the TAM theory by developing perceived usefulness to explain the rational dimension and incorporates perceived coolness to explain the emotional dimension.

Secondly, given the inherent high risk in online communication, the development of the mediating variables (satisfaction) becomes a crucial consideration for understanding the reasons why users continue utilizing AI chatbots. Furthermore, this research extends prior studies on AI chatbot adoption by observing the relationship between satisfaction to account for user expectations and post-usage experience. When combined with the extended TAM variables, these mediators provide a more holistic understanding to explain the continuance intention regarding AI chatbot usage.

Finally, this research enriches the literature in the fields of business and healthcare, specifically concerning AI chatbot adoption, by integrating both rational and emotional factors within the Indonesian context. Research on the adoption of AI chatbots in the healthcare sector is still relatively limited (Ashfaq et al. 2020; Esmaeilzadeh et al. 2025), and the number of studies in Indonesia remains very small, although it is beginning to grow significantly. Nevertheless, a research model that provides a holistic view to understand the reasons/intentions for an individual to continue using an AI Chatbot is very valuable.

Practical Implications

Practically, this research provides implications for the healthcare sector, business, and technology developers to enhance the system performance of generative AI, particularly AI Chatbots, across both rational and emotional aspects. In the healthcare sector, the research findings indicate that the rational influence (perceived usefulness) is weaker compared to the emotional aspect. In the context of healthcare services in Indonesia, perceived coolness is considered a critical factor influencing the intention to continue using the AI chatbot. While not underestimating the rational aspect, to maintain and increase the intention to continue usage, AI designers and administrators must emphasize chatbot services with positive human emotion, such as empathy and high responsiveness. Unlike other industries, such as the business or education sectors, the role of the emotional aspect might be smaller in influencing adoption decisions. However, in the healthcare domain, because it concerns health issues, life risks, and high costs, users are tended to prioritize the emotional aspect provided by the AI Chatbot.

CONCLUSION

By using the TAM and ECM framework, this research combines rational and emotional variables to better predict continuance intention to use an AI Chatbot in health care services. Specifically, the rational variables were represented by perceived usefulness, and the emotional variable by perceived coolness. The ECM theory was utilized to understand the intention for continued use of the technology. Within the healthcare sector, this study found that both the rational and emotional aspects significantly contribute to the continuance intention of AI chatbot usage. The rational aspects, which were represented primarily by Perceived Usefulness, is highly crucial in building satisfaction, and consequently, determine the intention to continue using the AI chatbot in healthcare services.

While this study provides valuable insights into the field of technology adoption, its limitations open avenues for future research. First, the primary limitation of this study is the sample usage, which was focused mainly on distribution in large cities in Indonesia, primarily due to more accessible internet connectivity and the presence of healthcare facilities (hospitals) that have already deployed AI chatbot services. To improve generalizability, future research should aim to reach smaller cities in regional areas to observe the benefits and acceptance of AI services more widely in the healthcare sector. Second, this AI chatbot study utilized a quantitative approach and distributed questionnaires to the general public who use healthcare AI chatbots. Consequently, it does not represent the perspectives of AI system administrators and developers. Future research could conduct studies from two sides, both user communities and healthcare service providers, to enhance AI chatbot quality. Third, consumer users were selected using a purposive sampling method, which has the potential for bias in respondent selection and thus may limit the generalizability of the conclusions in this study's findings.

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