“Determinants of consumers’ emotions and willingness to use artificial intelligence in Indonesia”

AUTHORS	Dwinita Laksmidewi Efendi Wong Chee Hoo

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Dwinita Laksmidewi (Indonesia), **Efendi** (Indonesia), **Wong Chee Hoo** (Malaysia)

DETERMINANTS OF CONSUMERS' EMOTIONS AND WILLINGNESS TO USE ARTIFICIAL INTELLIGENCE IN INDONESIA

Abstract

This research examines the key factors influencing Indonesian consumer' willingness to use AI chatbots, focusing on technological characteristics, hedonic motivations, anthropomorphism, AI performance and user experience, using the extended Artificially Intelligent Device Usage Acceptance (AIDUA) model. This is quantitative research where a survey technique was adopted, and two hundred and eight participants' responses were obtained. The participants were consumers in Indonesia who had prior experience using AI chatbot. The study reveals that anthropomorphism, technological competence, and consumer hedonic motivation while using a chatbot affects the consumer's perception about the perceived performance of a chatbot and the user experience. These perceived performance and experiences influence feelings, and then influence the willingness to use the AI chatbot. Mediation analysis indicated that perceived performance mediated the relationship between anthropomorphism and willingness to use AI, while user experience did not. That hedonic motivation affects willingness to adopt AI through the mediations of user experience, emotions, and perceived performance. Further, technological factors influence willingness to use AI mediated by perceived performance, in which case, user experience is not a mediator. The results indicate that the factors influencing the willingness to use AI include technological readiness, anthropomorphism, and hedonic motivation, which are mediated by perceived performance and emotions, whereas user experience does not significantly mediate the relationship.

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Dwinita Laksmidewi, Faculty of Economics and Business, Universitas Katolik Indonesia Atma Jaya [Atma Jaya Catholic University of Indonesia], Indonesia. (Corresponding author)

Efendi, Faculty of Economics and Business, Universitas Katolik Indonesia Atma Jaya [Atma Jaya Catholic University of Indonesia], Indonesia.

Wong Chee Hoo, Dr., Associate Professor, Faculty of Business and Communications, INTI International University, Malaysia.

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INTRODUCTION

Artificial Intelligence (AI) has expanded as a field in the last few years, and so has the application of AI in customer service and it brings operational efficiency and cost savings, as well as optimal automation of processes to deliver consumer-oriented solutions (Gursoy et al., 2019). AI-based service agents are utilized by companies and public authorities to mediate the interaction between the consumers and the contact centres for the businesses and over the chat, email, phone (Chi et.al., 2020). This kind of agents employs technologies such as NLP, as well as machine learning to carry out the process of interacting with consumers. AI in the consumer service sector largely helps in delivery of the Sustainable Development Goals by improving effectiveness, productivity and accessibility of services, which are key to the Sustainable Development Goals, given the dimensions of growth, sustainability, and innovation of services in this sector.

In Indonesia, AI service agents are deployed across a range of industries, including healthcare, education, banking, and telecommunications, with adoption accelerating during the COVID-19 pandemic due

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to the need to minimize physical contact (De, 2018; Laksmidewi & Gunawan, 2023). Despite these advances, many consumers in Indonesia still prefer human interaction over AI-based services, largely due to trust issues and AI's limitations in responding to emotions, especially when handling complaints (Mozafari et al., 2022; Crolic et al., 2022). This study addresses this gap by exploring why consumers prefer human services over chatbots, focusing on the role of technology and user experience factors.

When chatbots exhibit more natural language, emotional responses, or human-like behavior, interactions become more enjoyable and personal. This leads consumers to perceive these chatbots as more effective and responsive, resulting in positive emotional responses, such as feeling understood and valued. These positive emotions foster a stronger connection between consumers and AI technology, increasing the likelihood of continued use and adoption due to the engaging and human-like experience. However, Indonesian culture may influence the impact of anthropomorphism differently, as interpersonal relationships and social harmony are highly valued. Therefore, the AIUDA model needs to be specifically adapted for the Indonesian context to better align with local values and consumer expectations.

1. LITERATURE REVIEW AND HYPOTHESES

Artificial Intelligence Service Agents (AISA) are becoming increasingly integrated into various service industries, replacing traditional human-operated services on platforms such as websites, mobile applications, and telephony (Yang et al., 2022). These AI-driven agents, which include smart devices, self-service technologies, chatbots, and service robots, offer companies a new avenue to enhance customer comfort and satisfaction (Chi et al., 2020). The widespread adoption of chatbots by businesses of all sizes underscores their potential to improve service efficiency, especially in industries such as tourism (Um et al., 2020) and banking (Lee & Chen, 2022). However, while chatbots can enhance customer service and reduce operational costs (De, 2018), there are concerns that they may also compromise the quality of customer interactions and lead to negative experiences (Crolic et al., 2022). This presents a critical challenge for marketers to design chatbots that effectively balance these benefits and drawbacks.

The challenge of chatbot design can be partially addressed by leveraging anthropomorphism, the human tendency to attribute human-like characteristics to non-human entities (Epley et al., 2007). Anthropomorphism plays a pivotal role in making AI service agents more relatable and acceptable to consumers, as it helps bridge the gap between human and machine interactions. Consumers are more likely to perceive AI agents positively when these agents exhibit human-like traits, such as recognizing emotions and communicating effectively (Gray et al., 2007). This heightened perception often leads consumers to believe that AI agents can perform at a level comparable to humans (Waytz et al., 2010). Besides, the research suggests that when the chatbot is more humanized, in that they are given more human sounding names, this increases the levels of consumer satisfaction (Crolic et al., 2022). This implies that anthropomorphism not only increases the perceived performance of a chatbot, but also the communication overall, thus making interaction with technology a better experience. That is why anthropomorphism not only increases the satisfaction with the chatbot's performance but also helps to provide the overall positive experience of interaction with AI (Vitezić & Perić, 2021).

For instance, research by Liu et al. (2021) emphasizes that anthropomorphic design elements in AI applications significantly enhance users' perceptions of performance and trust. Their study found that human-like interactions increase users' confidence in the capabilities of AI systems, thereby promoting continued use and engagement. Similarly, Li et al. (2022) discovered that anthropomorphism in AI interfaces helps bridge the gap between users and technology, leading to more natural and effective interactions (Liu et al., 2021; Li et al., 2022).

On the same note as the user experience concept, another theory known as hedonic motivation helps explain how consumers engage with

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the AI service agents. Hedonic consumption is different from utilitarian consumption in that the former involves achievement of hedonic or sensory benefits (Longoni & Cian, 2022). When it comes to AI hedonic features can improve the level of usage of service-agents as they contain elements that are exciting and can bring joy to the user (Cabrera-Sánchez et al., 2021). Such enjoyable interactions are necessary for the formation of positive affects towards the AI, which in a turn leads to repeated use and enhanced level of perceived satisfaction with the service (Lin et al., 2020). Kim and Lee (2017) and Venkatesh and Bala (2008) highlight that users' enjoyment of a technology interface positively affects their overall experience and willingness to engage with the technology. Hedonic aspects added into AI service agents therefore enhances the anthropomorphic design, enhancing the user perceptive and experience (Gursoy et al., 2019).

Despite all these, technological factors remain the main barriers to expanding AI services. Some consumers are still sceptical to use AI because of technophobia, perceived technological competence and fear for their data protection (Gursoy et al., 2019; Parasuraman & Colby, 2015). This resistance is among the reasons why there is a need for more than anthropomorphic and hedonic AI systems: the AI systems also have to be secure, straightforward to use. Mitigating such technological issues, it is crucial for countering consumer resistance and placing AI service agents back in the category of credible and effective tools (Lin et al., 2020).

These technological concerns have a direct impact on the level of perceived performance of AI systems and therefore on the consumer's emotions and the readiness to use AI services. According to the Technology Acceptance Model (TAM), the usage of new technologies is a result of the perceived usefulness and perceived ease of use (Venkatesh et al., 2003). The study in the case of AI service agents suggests that perceived performance most definitely in terms of benefits and ease of its use can also have a bearing on emotional effect. Engaging with AI and feeling that the AI initiative is satisfactory will result in positive affect and these in turn will increase the likelihood of relying on the AI services in the future (Lai et al., 2021). This is made possible by the ideas of parasocial interaction in which consumers develop one-way emotional relationships with AI entities because of their anthropomorphic qualities (Noor et al., 2021). Technological improvements influence how users regarding the capabilities of artificial intelligence, resulting in more effective positive customer emotions that promote the use of AI (Kim & Lee, 2022; Wang et al., 2023). The research by Singh et al. (2022) showed that although users may perceive a technological system as useful, their enjoyment of the experience does not necessarily drive their engagement or desire to use the technology further.

The anthropomorphic chatbot design is expected to replace human services, so it is thought to affect perceived performance and user experience. Likewise, the technological readiness factor from the consumer side and the hedonic aspect of the AI service are thought to also affect the assessment of performance and experience. The perceived performance of the AI chatbot and the user experience create positive emotions that then create a desire to use the AI chatbot in the future.

The study aims to examine the determinant variables of willingness to use AI, thereby providing an understanding of the key factors that drive AI adoption. Therefore, the following hypotheses are formulated:

H1: *Chatbot anthropomorphism influences the perceived performance of chatbots.*

H2: *Chatbot anthropomorphism influences user experiences.*

H3: *Hedonic motivation influences the perceived performance of chatbots.*

H4: *Hedonic motivation influences user experiences.*

H5: *Technological factors influence the perceived performance of chatbots.*

H6: *Technological factors influence user experiences.*

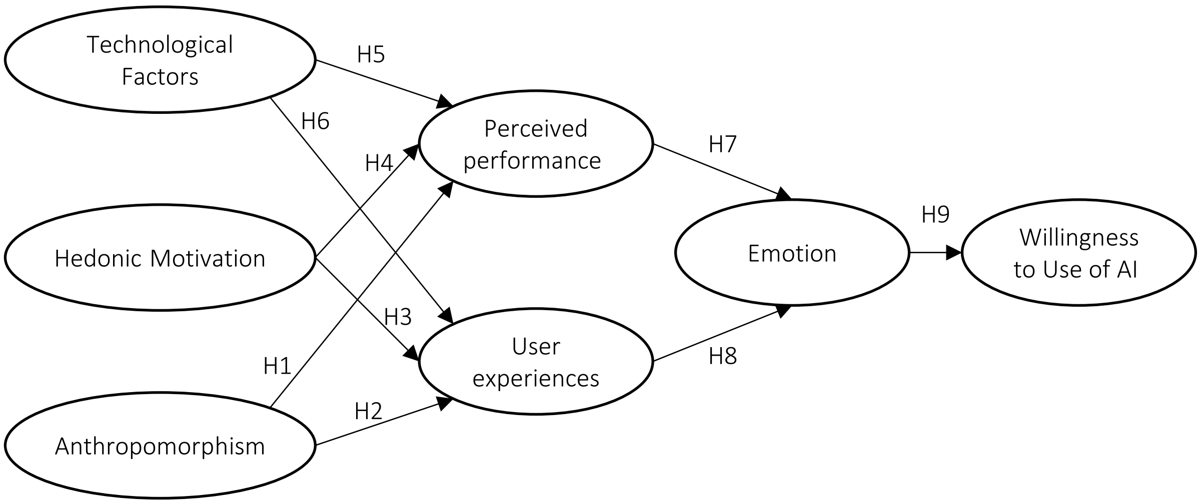

Figure 1. Research model – determinants of consumers' willingness to use AI

H7: Perceived performance influences consumer emotions.

H8: Users experience influences consumer emotions.

H9: Consumer emotions influence the willingness to adopt AI.

2. METHODOLOGY

The study was carried out in Indonesia. The participants totalled two hundred and eight, and all the participants had prior use of chatbot service. In this study, the concentration was made on chatbot AI agents and purposive sampling was used to select participants who have experienced the use of a chatbot. The respondents were at first asked a general question on the name of the chatbot that they frequently used to make sure that the following questions corresponded to the experiences with the chatbot.

Data collection was done via Google Forms since much of testing and communication happens online today, and any participant in the world could respond. The reliability and validity of the instrument were assessed before the administration of the questionnaire through a pilot test. In the available pretest results, all sorts of indicators showing that all developed indicators were both valid and reliable since the Cronbach's Alpha values were above of 0,7, indicating strong internal consistency.

The study involved the use of several constructs, and the instruments used in measuring them were adapted questionnaires. Anthropomorphism was assessed with three items adapted from Melián-González (2021): Some of the indicators made include, "Chat with chatbots look like a conversation with a person," "Chatbots look like they know the people they are interacting with," and "It feels natural to chat with chatbots." Hedonic motivation, willingness using AI developed from Gursoy et al. (2019) and emotion using the emotions scale developed by the same authors. The perceived performance was established by measuring it with an instrument with items such as 'Chatbots increase my performance' and 'Chatbots provide access to better quality information'. Finally, user experience was measured by an instrument adapted from Te Pas et al. (2020). Each item in the seven constructs was scored using a six-point Likert scale. For the analysis of the test results and the data analyses, SmartPLS software was employed for testing the hypotheses set and constituted an appropriate tool for analysing complex models.

The respondent profile shown in the Table 1 presents them as young and urban people, 77.4% fell in the 17-22 years age group and 83.2% of them are students, many of whom are from Jakarta and its vicinity. 9% have used chatbots in their operations most of which are Telkomsel,

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Veronika, ChatGPT, and Shopee. This shows that they are conversant with products that apply chatbot services and hence the importance of the chatbot services in their day-to-day lives.

Table 1. Respondents

Characteristics of respondents		Total	Percentage
Gender	Male	105	50.5%
	Female	103	49.5%
Age	17-22	161	77.4%
	23-30	23	11.1%
	31-50	15	7.2%
	>50	9	4.3%
Occupation	Student	173	83.2%
	Private employees	23	11.1%
	Businessman	6	2.9%
	Housewife	4	1.9%
	Government employees	2	1%
Domicile	Jakarta	124	59.6%
	Tangerang	36	17.3%
	Bekasi	22	10.6%
	Bogor	9	4.3%
	Depok	8	3.8%
	Bandung	2	1.9%
	Jayapura	2	1.9%
	Dilli	2	1.9%
	Karawang	1	1%
	Palembang	1	1%
	Ende	1	1%
Have you ever used a chatbot?	Yes	162	77.9%
	No	46	22.1%
Chatbots that have been used	Veronika, Telkomsel	37	35,57%
	Chatgpt	25	24,04%
	Shopee	10	9,6%
	Vira, BCA	5	4,8%
	Siri, Apple	6	5,7%
	MyAI, Snapchat	7	6,7%
	Jeklin, Gojek	6	5,7%
	Maya, XL	5	4,8%
	Grab	3	2,8%

3. RESULTS

This results section will present an in-depth analysis of the determinants of AI willingness to use in the future. The findings are based on quantitative analysis using the survey method, which begins with testing the validity and reliability of the model, then followed by hypothesis testing and its analysis.

Two items of the anthropomorphism variable indicated outer loadings less than 0,7 in the first phase of outer loading testing: Antro 2 which has a factor loading of 0. 698 and Antro 5 which has a factor loading of 0. 605. Similarly, the factor loadings that were lower than the threshold were User 1 with factor loading equal to 0. 357 and User 2 with factor loading equal to 0. 534 all of them being part of the variable user experience. Thus, these four indicators were dropped out of testing any further. As described in Table 2 further evaluation showed that all remaining indicator loadings exceeded 0.7 as these confirm the construct validity of the scale.

In testing discriminant validity, the Fornell and Larcker criteria as adopted by Hair et al. (2014) was used by the author. Discriminant validity is when the approximately square root of the Average Variance Extracted (AVE) is significantly higher than another variable. As shown in Table 3, the AVE values for each of the variables are above 0.5 and exceed the other variable relations.

Table 2. Convergent validity

Variable	Indicator	Outer loading
Antropomorphism	Antro1	0,771
	Antro3	0,830
	Antro4	0,801
Emotion	Emo1	0,854
	Emo2	0,858
	Emo3	0,908
	Emo4	0,892
Hedonic motivation	Hed1	0,872
	Hed2	0,928
	Hed3	0,904
	Hed4	0,941
Perceived performance	Perf1	0,877
	Perf2	0,898
	Perf3	0,834
	Perf4	0,851
Technology factor	Tech1	0,766
	Tech2	0,761
	Tech3	0,763
	Tech4	0,710
User experience	User3	0,891
	User4	0,841
Willingness to use AI	Will1	0,854
	Will2	0,888
	Will3	0,878
	Will4	0,741

Table 3. Several criteria for the outer model and inner model

Variable	Outer model		Inner model				
	AVE	Cronbach's Alpha	R^2	F^2			
				Perceived perform	User exp	Emotion	Will to use AI
Antropomorphism	0.801	0.725		0.032	0.031		
Technology factor	0.867	0.891		0.054	0.027		
Hedonic motivation	0.912	0.932		0.210	0.057		
Perceived performance	0.866	0.888	0.441			0.301	
User experience	0.867	0.671	0.249			0.061	
Emotion	0.878	0.901	0.398				0.984
Willingness to use AI	0.842	0.862	0.496				

The reliability test (Table 3) shows that all the variables have Cronbach's Alpha of more than 0.6, signifying satisfactory reliability. Additionally, in order to check multi-collinearity, the focus was shifted towards VIF values and those values also came out to be reasonable. Hair et al (2014) opined that VIF values should be below 5 to indicate that collinearity is not a big problem. The collinearity test used to show that all VIFs are less than 5; hence, no issue of collinearity.

When evaluating the inner model, the authors examine relationship significance between constructs/variables, as indicated by the path coefficient (Figure 2). Prior to this, the author conducted R^2 and Goodness of Fit (GoF) tests (Table 3) to validate the overall research model. Several criteria must be met to decide if the research model is fit. In the model developed, the SRMR value is 0.061, which is below 0.10 or ideally below 0.08, indicating a good fit (Hu & Bentler, 1999). The NFI value is 0.788, with the Normed Fit Index (NFI) ranging between 0 and 1; the closer it is to 1, the better, and if above 0.9, it is generally considered an "acceptable fit," suggesting the model is good. The Chi-Square value (X^2) divided by the degree of freedom (df) must be below 5 to be considered a "good fit"; in this model, X^2 = 3.9451, indicating a good fit. The GoF measure also indicates a good fit; therefore, the research model is considered good.

The R^2 value of 0.441 for perceived performance indicates that the model assessing the influence of anthropomorphism, technological factors, and hedonic motivation on perceived performance can be considered good (moderate). Similarly, the R^2 value of 0.249 for the model assessing the influence of anthropomorphism, technological factors, and hedonic motivation on user experience is

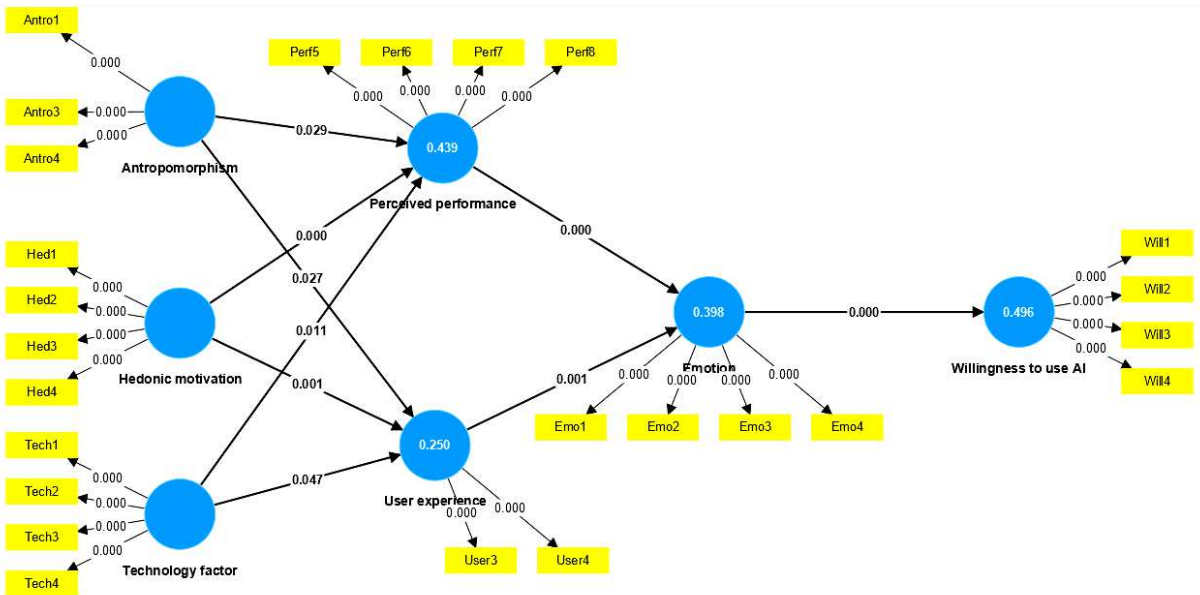

Figure 2. Path coefficient and p-value

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Table 4. Direct effect

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-statistics (|O/STDEV|)	p-value
Antropomorphism → Perceived performance	0.173	0.178	0.079	2.181	0.029
Antropomorphism → User experience	0.195	0.201	0.088	2.212	0.027
Emotion → Willingness to use AI	0.704	0.705	0.045	15.487	0.000
Hedonic motivation → Perceived performance	0.451	0.446	0.082	5.511	0.000
Hedonic motivation → User experience	0.271	0.266	0.080	3.410	0.001
Perceived performance → Emotion	0.490	0.495	0.059	8.275	0.000
Technology factor → Perceived performance	0.180	0.187	0.071	2.534	0.011
Technology factor → User experience	0.156	0.162	0.079	1.990	0.047
User experience → Emotion	0.222	0.216	0.067	3.303	0.001

weak (R^2 value of 0.25 falls within the weak category) Hair et al., 2011). Together, Perceived performance and user experience can explain emotion by 39.2%. Furthermore, all models combined can explain the willingness to use AI by 49.3%, falling into the moderate category (with R^2 value of 0.50, categorized as moderate).

Hedonic motivation emerges as the variable with the strongest influence on perceived performance (F^2 = 0.210, indicating a quite strong influence) (Table 3). An F^2 value of 0.02 is classified as a weak influence, 0.15 as a sufficient influence, and 0.35 as a strong influence on exogenous variables in the structural model (Hair et al., 2017). Similarly, hedonic motivation also exhibits the strongest influence on user experience, albeit with a relatively weak impact (F^2 = 0.057). Perceived performance exerts a strong effect on emotion (F^2 = 0.301), surpassing the influence of user experience, which has a weaker effect on emotion. Furthermore, the influence of emotions on willingness to use AI is categorized as very strong (F^2 = 0.984).

The research on direct effect uncovers the following interesting insights about the relationships model of anthropomorphism, hedonic motivation, technology factors, perceived performance, user experience, and emotions in the adoption of AI. First, the present research finds that anthropomorphism has a positive impact on perceived performance (t = 2.181, p = 0.029) and user experience (t = 2.212, p = 0.027) thus supporting Hypotheses 1 and 2. This implies that when the AI agents especially the chatbots are endowed with human like features, their performance is thought to be better and likely to offer the user a better experience. The anthropomorphism effect is in harmony with the belief that endowing AI with human qualities improves the interface experience by making it more like the one with other people.

Likewise, there is a positive and strongly significant correlation of hedonic motivation with perceived performance (t = 5.511, p = 0.000) and the user experience (t = 3.410, p = 0.001), hence accepting Hypotheses 3 and 4. This suggests that the emotional satisfaction and fun, which users get from the usage of AI systems boosts their appreciation of the AI system's performance, as well as their experience. Hedonic motivation seems to play a vital role in explaining the way that users perceive the benefits and pleasures of engaging with AI technologies.

Technology factors also have large effects, perceived performance and user experience are positive impacted, Hypotheses 5 and 6 are supported (t = 2.534, p = 0.011; t = 1.990, p = 0.047). This goes further to show that components that are technically oriented like usability and utility influences AI competence and utilization by the user. When choosing technological interfaces, it becomes possible to improve both, the satisfaction of the user, as well as the functioning of the AI system.

Perceived performance has a significant positive relationship with emotions (t = 8. 275, p = 0.000) and the same is true for user experience/ satisfaction (t=15.487, p=0.001). Therefore, Hypotheses 7 and 8 can be accepted. Further, while the positive emotions will be achieved with high performance and experience, this indicates that users are likely to develop positive attitude towards AI systems because of effectiveness and fun while using.

Last but not the least, Hypothesis 9 postulates positive influence of emotions on the willingness to use AI (t = 3.427, p = 0.000); therefore, it is accepted. Emotional responses therefore are crucial in determining the patrons' continued use of these technologies. When users have some sort of positive emotional responses to it, they will foster the use of such artificial intelligence systems in their daily lives. In other words, anthropomorphism, hedonic motivation and technology aspects can have direct influence on perceived performance and experience, which leads to emotions. They then influence user's decisions to accept or shun the use of AI, which is the next phase that must be discussed. Accordingly, based on this research, it becomes possible to improve the anthropomorphic features and make the user interfaced more entertaining and appealing to the user while fine-tuning the technological aspect can make a difference in the perceived performance, user satisfaction and satisfaction of emotion that in turn results in increased tendency to adopt the AI.

As for a further analysis, more elaborate mediation testing was performed within this research model. The indirect effect path analysis revealed that most of the paths were significant, indicating a strong relationship between the studied variables. However, two indirect paths namely Anthropomorphism → User experience → Emotion → Willingness to use AI and Technology factor → User experience → Emotion → Willingness to use AI both were insignificant as evident from t-values of 1.228 (p = 0.038) and 1.711 (p = 0.087), 639 (p = 0.101), respectively. This means that there is no correlation between anthropomorphism and people's willingness to use AI through the mediation role of user experience and emotional response to technology.

Further, the paths Anthropomorphism → User experience → Emotion (t = 1.780, p = 0.075) and Technology factor → User experience → Emotion (t = 1.682, p = 0.093) were non-significant. These results imply that while anthropomorphism and technological factors can directly influence user experiences and emotions, their influence does not extend significantly beyond these mediating variables.

This analysis suggests that while some direct effects may exist, complex mediation pathways involving user experience, and emotions do not play a substantial role in translating the impact of anthropomorphism and technological factors into increased willingness to adopt AI.

Table 5. Indirect effect

Variable	Original sample	Sample mean	Standard deviation	t-statistics	p-values
Technology factor → Perceived performance → Emotion	0.088	0.093	0.038	2.298	0.022
Antropomorphism → User experience → Emotion → Willingness to use AI	0.030	0.031	0.018	1.711	0.087
Hedonic motivation → User experience → Emotion → Willingness to use AI	0.042	0.041	0.020	2.103	0.036
Antropomorphism → Perceived performance → Emotion → Willingness to use AI	0.060	0.062	0.028	2.105	0.035
Perceived performance → Emotion → Willingness to use AI	0.345	0.350	0.053	6.550	0.000
Hedonic motivation → Perceived performance → Emotion → Willingness to use AI	0.156	0.157	0.041	3.799	0.000
Technology factor → User experience → Emotion → Willingness to use AI	0.024	0.025	0.015	1.639	0.101
User experience → Emotion → Willingness to use AI	0.156	0.154	0.051	3.034	0.002
Technology factor → Perceived performance → Emotion → Willingness to use AI	0.062	0.066	0.028	2.213	0.027
Antropomorphism → User experience → Emotion	0.043	0.044	0.024	1.780	0.075
Antropomorphism → Perceived performance → Emotion	0.085	0.088	0.040	2.133	0.033
Hedonic motivation → User experience → Emotion	0.060	0.058	0.027	2.241	0.025
Hedonic motivation → Perceived performance → Emotion	0.221	0.222	0.053	4.177	0.000
Technology factor → User experience → Emotion	0.035	0.035	0.021	1.682	0.093

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4. DISCUSSION

An analysis of the path model shows that there is a positive association between hedonic motivation, user experience, emotion, and willingness to use AI. The implications of the current research underscore how the hedonic motivation, resulting from chatbot experiences, influences consumer behaviors in the AI environment. Hedonic motivation can be defined as the enjoyment that users have when engaging themselves with the chatbots, thus providing the users with positive attitudes towards the use of chatbots. Hedonic motivation contributes greatly to enhancing user engagement and satisfaction. These results support previous research that hedonic motivation significantly influences user engagement with digital services, emphasizing that pleasurable interactions lead to heightened satisfaction and continued technology use (Kim & Lee, 2017).

The results also indicate that enjoyable and efficient chatbot interactions foster positive emotions, including relaxation, hopefulness, happiness, and satisfaction. This aligns with findings by Dinh and Park (2023), who demonstrate that user satisfaction with AI technologies is closely linked to positive emotional experiences. They argue that AI systems perceived as entertaining and responsive are more likely to create favorable emotional responses and increase user willingness to adopt the technology (Dinh & Park, 2023). The correlation between hedonic motivation and user experience underscores the importance of designing chatbots that prioritize enjoyable and convenient interactions. This finding is consistent with previous research by Kaplan and Haenlein (2019), who emphasize that enhancing the pleasure aspect of technology can significantly influence user attitudes and behavior towards AI systems. Their study indicates that a focus on user satisfaction and convenience can drive higher adoption rates and sustained engagement with AI-driven services (Kaplan & Haenlein, 2019). The result indicates a significant influence of hedonic motivation on the desire to use AI by shaping perceptions of performance. Engaging with chatbots in a pleasurable manner enhances users' performance and aids in task completion while improving information acquisition.

Hedonic motivation, which describes the joy that people obtain from the interactions, affects also the perception of performance. Tarafdar et al. (2020) also confirmed that users who can have fun while using the applications resulting to better assessments of their performance and higher usage intentions. In the same respect, the study carried out by Lee et al. (2021) provides evidence validating the proposition that hedonic technologies affect users' perceptions and corresponding behavior. They discovered that pleasure obtained from using technology plays an additional role in both working effectiveness and users' tendency to continue to patronize the technology.

Many effects of anthropomorphism are instrumental in modifying users' intentions to use the AI technology depending on how they perceive its performance. When the chatbot acts more human-like, by giving the impression that it comprehends the user, and provides valuable, genuine interactions, the consumer is convinced that AI systems can perform better, help in the completion of a particular task, and can help in decision-making. On this account, the given perception of an improvement of their present performance leads to positive feelings that further increases the likelihood of repeating the use of chatbots in the future.

However, as mentioned above regarding the effect of anthropomorphism, although users' perceptions of the systems' performance are increased, this is not necessarily reflected in perceptions of ease and speed. Users may not be able to feel that by engaging with the anthropomorphic chatbots that he or she is interacting with an entity that is faster or more efficient that a human one. From this work, it can be inferred that even though the people liked the idea of humanlike qualities in AI, it still lacks the efficient and convenient perception. Lee et al. (2022) concur with this finding and found that anthropomorphism improves the user satisfaction and engagement with the system, but it does not necessarily mean that the user will perceive the system itself as being more efficient as well.

These results highlight a critical consideration for AI developers: although endowing designs with human-like qualities would serve to make users trust the AI and interact with it more often, that factor does not inflate perceptions of efficiency. The developers should thus consider a middle line involving insertions of anthropomorphic features and at the same time, the speed and efficiencies of the interaction. This procedure ensures that the experiences AI systems offer to its users are not only entertaining but also useful.

In the context of user experience, although users reported that learning and proceeding through the process of interacting with AI was easy and fun, which are technological factors we can presume, these do not actually see the interactions as faster or easier. This discovery appears to indicate that how people interact with AI – via technological literacy – can make such systems more understandable but may not improve feelings of satisfaction or improved user experience. Some modern studies can be also mentioned as far as they follow this line of thought. This finding is in line with Zhang et al. (2022) who identified that although the integration of such technologies increases the ease of use of AI systems, it may not improve the feelings associated with using the system.

However, it was also established that technological factors have impact on users' perception of the performance of chatbot. Also, as an application of AI technologies increases, users, considering the performance indicators, experience positive attitudes and emotions and will interact with chatbots in the future. This goes to show that technological capability plays a central role in influencing users' perception and attitude in the uptake of innovation. Based on the observations developers should target and emphasize not only the growth of technologies of AI systems but also the pleasure and intuitive interface.

It is pertinent to mention that this research differs from the previous research as it has considered the user experience and technology factors as the two important variables due to the technological environment in Indonesia. In contrast to the previous research, this study does not show that the user experience variable is significant, meaning that Indonesian consumers are not using AI for fun, but for need. Nevertheless, this study departs from this trend in that it does not consider social influence as is highlighted in Lin et al. (2020) and Gursoy et al. (2019). On the other hand, this research model does not have social influence because in the culture of Indonesia the social factors are sometimes latent factors in the society and do not need to be modelled.

The findings of this study are consistent with the literature showing that although hedonic motivation has a positive impact on performance and perceived emotions, user experience may not always correlate with enjoyment. The studies suggest that there is a need for both scholars and practitioners to consider culture and context of their specific settings to design 'good 'AI. Thus, the Indonesian approach may stand more to benefit from accentuating the functionality and correspondingly matching AI capabilities with the users' requirements than from simply pursuing the satisfaction of entertainment purposes.

CONCLUSION

This study shows that the AI adoption process is determined by technological factors, hedonic motivations and anthropomorphism, where these factors influence the perception of performance. The sophisticated exchange of messages in speech with a chatbot (anthropomorphism) based on the system's ability to understand and respond, leads to positive emotions and a desire to interact with the AI system in the future. However, this is not the case in terms of the perceived ease or speed of interaction. Hedonic motivation has been shown to positively affect both perceived performance and user experience, aligning with previous research that emphasizes the importance of enjoyable interactions in driving user engagement with AI.

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This study also provides insight into the emotional response of users to the acceptance of AI, which can lead to increased use and adoption of AI-based chatbots. Technological factors do not significantly affect the user experience in terms of emotional responses, based on this the authors argue that it is not enough to only highlight the technological aspects of the application; developers should pay more attention to the usability and emotional appeal of the application.

Future research is recommended to consider how cultural factors may or may not play a role in how users interact with AI. The cultural context can influence the level of hedonic and utilitarian motives and that is why it is important to study these differences in order to predict how AI solutions will be perceived and used by different people. Besides, developers should pay attention to the increase in the perceived utilitarian aspect of the interaction with AI. Thus, if anthropomorphism data and perceived emotional satisfaction are complemented by a technically optimal AI system, overall acceptance will increase. Although this study did not control and test the social influence variable for AI adoption, future research in examining the social influence construct to determine the impact on AI adoption in different cultures may yield useful information.

AUTHOR CONTRIBUTIONS

Conceptualization: Dwinita Laksmidewi, Efendi.
Formal analysis: Dwinita Laksmidewi, Efendi.
Funding acquisition: Dwinita Laksmidewi, Wong Chee Hoo.
Data collection: Dwinita Laksmidewi, Efendi.
Methodology: Dwinita Laksmidewi, Efendi.
Project administration: Efendi.
Resources: Efendi, Wong Chee Hoo.
Software: Dwinita Laksmidewi, Efendi.
Supervision: Dwinita Laksmidewi.
Writing – original draft: Dwinita Laksmidewi, Efendi, Wong Chee Hoo.
Writing – review & editing: Dwinita Laksmidewi, Efendi, Wong Chee Hoo.

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