The Influence of AI Chatbot Interaction Styles on User Acceptance

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***Abstract*—This study provides an overview of how AI Chatbot interaction styles, particularly anthropomorphic interaction style influences user acceptance. Previous studies have explored about the role of anthropomorphic or human-like AI Chatbot interaction to improve user engagement but its influence on user acceptance is underexplored. Through a survey of 300 participants, the study analyses user preference towards anthropomorphic or non-anthropomorphic interaction styles with statistical analysis of quantitative data using independent samples t-test, Cohen's d and multiple regression analysis. The analysis supports our hypothesis that the users tend to show higher acceptance towards AI Chatbots with anthropomorphic interaction styles. Additionally, the findings suggest that the anthropomorphic interaction style positively influences user acceptance especially among the younger and highly educated demographic.**

***Index Terms*—AI, Chatbots, Human-like, Anthropomorphism, Human-AI Interaction (HAII), User Acceptance**

I. Introduction

AI chatbots are used in a large scale recently, due to developments in AI and machine learning. They represent interactive systems in which Human-Computer-Interaction (HCI) takes place and can communicate using natural languages. They are used in diverse sectors like health, education, entertainment, marketing etc. and can imitate human behavior and conversational conditions [1]. *Anthropomorphism is defined as the assignment of human-like traits, behaviours, or mental states to non-human entities like objects, brands, animals, and, recently, technological devices.* The psychological anthropomorphic characteristics of an AI chatbot along with its empathetic and interactive capabilities makes it more likely to be accepted by a user [2]. This study analyses the impact of different interaction styles of AI chatbots, focusing mainly on anthropomorphic interaction style and how it influences user acceptance. Based on survey data to investigate user preferences towards this interaction style, contribution of factors like trust, engagement and satisfaction for the overall acceptance is examined. To guide this investigation, the research question is: What is the influence of different interaction styles of AI chatbots on User Acceptance? The hypothesis theorized is: Users tend to show higher acceptance towards AI chatbots with anthropomorphic interaction styles.

II. Literature Review

A. Human-AI Interaction (HAII).

The rise in AI-driven technologies has transitioned typical HCI to a newer field called Human-AI Interaction (HAII) which focuses on the study of interaction between AI computing systems and humans. HAII is dependent on two key factors: Human-AI fit which means how well an AI meets physical, cognitive and emotional needs, and Task-AI fit which means an AI's capability to perform certain tasks. Depending on a user's needs and tasks, HAII ranges from full human control to full AI control [3]. The previous works related to HAII focused primarily on intermittent interaction style which is a turn-taking process where the interaction occurs between the AI system and the user in turns. It is a process where the user constantly provides input and evaluates the feedback from the system until the final goal is achieved. However, new studies highlight continuous interaction style, which is a process where the AI system handles user input in real time and provides ongoing feedback throughout the task. This allows the user to stay focused while the AI assists without interrupting the workflow. Similarly, proactive interaction style is presented where the AI system autonomously initiates and completes actions based on contextual data. This shifts the user's role from actively performing tasks to reacting to or adjusting the system's automated decisions. The HCI community has not broadly engaged with the ideas of continuous and proactive HAII whereas intermittent HAII is already a widely established concept [4].

B. Human-Likeliness or Anthropomorphism in an AI-Chatbot.

An AI-Chatbot or Conversational Agent (CA) can be perceived as human-like if it can conversate using natural language. A study shows that when participants were presented with simulated conversations between an AI and a user across different contexts, they were more likely to judge the AI as a human-like teammate under the conditions that they saw more conversations with it, they were less afraid of robots, and they trusted others more in general. Human-like characteristics of the AI deemed it to be more trustworthy, helpful and acceptable [5].The chatbots that mimic certain human traits like showing emotions or empathy, are likely to influence satisfaction, engagement and trust in different ways. Studies show that, an anthropomorphic chatbot can adjust its responses to better align with user expectations which creates a sense of understanding the user. Features such as emojis, active listening, or conversational tone make interactions feel more natural and relatable which increases the user's willingness to engage. Traits like assertiveness or social-oriented communication, can appear more trustworthy because they seem more capable of building relationships [6] [7] [8]. Similarly, research by Euodia Louis [9], mentions about source interactivity which is the ability of users to customize and have control over a platform via interactive features. It highlights studies about how interactivity and customization of AI Chatbots increases user engagement and satisfaction. AI Chatbots like Bing Copilot and ChatGPT allow users to adjust their conversational style to be more context-oriented and human-like and also adjust their responses according to user input. The one-way passive chat room scenario where the user starts a conversation is changed by this engagement between humans and AI chatbots. This makes interactions feel more authentic because AI Chatbots imitate human-conversational flexibility which is an anthropomorphic behavior.

C. Differences in User Acceptance of AI Chatbots.

Socio-cultural differences play a crucial role in technology acceptance, impacting key factors like perceived usefulness and ease of use, as outlined by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Studies by Zakour [10], and Srite and Karhanna [11], show that cultural dimensions such as individualism, collectivism, power distance, and uncertainty avoidance influence technology acceptance. In terms of chatbots, these cultural factors affect how users perceive interaction styles. Research by Van der Goot and Pilgrim [12], found that while both younger and older users are motivated by convenience, their needs for human contact and perceptions of security differ. These findings suggest that chatbot designs should account for cultural differences to enhance user acceptance [13]. Similarly, studies by Liu and Sundar [14], show that empathy and humour enhance user satisfaction and support user interaction. Fahdil and Schiavo [15], point out that a medical assistant that uses humorous or satirical approach was able to get a higher patient engagement. Although, humour is a universal approach, it is bound along with culture and language. It differs from culture to culture. A study conducted on empathy, humour and culture in conversational AI chatbots for second language acquisition shows that cultural dimensions improve communication, and culturally aware humour and empathetic responses resulted in positive experiences. Adding cultural nuances to AI chatbots helps for a wider socio-economic and cultural context which broadens user acceptance [16].

III. Methodology

The study used a wide range of survey data from 415 participants coming from diverse backgrounds. To establish a relation between the interaction style of the AI chatbot and user acceptance, we used relevant questions measured using the Likert scale which provided results in the form of interval data. We also provided an example of two different AI Chatbot responses, one anthropomorphic and the other non-anthropomorphic to evaluate the preference of the participants. We filtered the data because the response from 115 participants was invalid, and the final sample size was reduced to 300 participants.

TABLE I
GENDER FREQUENCY TABLE

Gender	Participants	Total
Female	118	300
Male	180	300
Diverse	2	300

Based on table I, there were 180 male participants, 118 female participants and 2 diverse participants. Besides the gender difference, the major responses came from the people below the age of 30, with significantly fewer responses from those above the age of 30. The highest number of participants, 172 were from the IT or Technological sectors whereas the remaining were from other professional sectors.

TABLE II
EDUCATIONAL ATTAINMENT FREQUENCY TABLE

Education	Participants	Total
Secondary Education/ High School	35	300
Vocational Training	8	300
Bachelor's or equivalent	191	300
Master's or equivalent	62	300
Doctorate or equivalent	1	300
Missing	3	300

Table II shows the distribution of participants based on their educational attainment, with the highest number of participants, 191 with a bachelor's degree followed by 62 participants with a master's degree. The lowest involvement is shown by PHD holders with a single participant. Apart from the difference in educational level, participants were from various religious backgrounds, with Hinduism on the top of the list with 103 participants, followed by Christianity with 77 participants whereas 32 participants did not follow any religion. This range of participants enables us to obtain a broad spectrum of user experiences which offers valuable insights into how AI chatbot interaction styles are perceived across different sociocultural backgrounds.

TABLE III
AI CHATBOT RESPONSE PREFERENCE FREQUENCY TABLE

Response	Participants	Total
Anthropomorphic style response	197	300
Non-anthropomorphic style response	103	300

We provided the participants with examples of anthropomorphic and non-anthropomorphic responses. As shown in table III, 197 participants preferred the anthropomorphic response whereas 103 preferred the non-anthropomorphic response. Besides this, we also provided six quantitative questions to evaluate the likeliness of participants to prefer a specific type of response. Two questions were inclined towards non-anthropomorphic AI chatbots whereas four towards anthropomorphic AI chatbots. We then calculated the mean of the six questions as the anthropomorphic preference score. Reverse encoding for the non-anthropomorphic response questions was carried out to ensure that we received accurate average score.

The study examined the responses using statistical analysis with JASP (Jeffreys's Amazing Statistics Program). We used analytical methods like the independent samples t-test, emphasizing on the preference of anthropomorphism. We used this particular method because the study aims to compare the anthropomorphic preference score which is the mean value of two independent sample groups where the first group prefers the anthropomorphic response while the second group prefers the non-anthropomorphic response. The data used as the measure for the independent variable is categorical or non-numeric with two levels; anthropomorphic and non-anthropomorphic, whereas the data used as the measure for the dependent variable is the anthropomorphic preference score which is continuous or numerical; derived as the average from the interval scale responses.

IV. Results

TABLE IV
INDEPENDENT SAMPLES T-TEST

	t	df	p
anthropomorphic_preference_score	6.887	141.685	$<$ .001

Note. Welch's t-test.

Table IV shows the results of the independent samples t-test. We used Welch's t-test due to unequal variances between groups, as indicated by the p-value <0.05 from the Brown-Forsythe test for equality of variances. The t-value is 6.887, with degrees of freedom (df) of 141.685. The p-value is <0.001.

TABLE V
INDEPENDENT SAMPLES T-TEST WITH EFFECT SIZE

	t	df	p	Cohen's d	SE Cohen's d
anthropomorphic_preference_score	6.887	141.685	$<$ .001	0.899	0.130

In addition to the independent samples t-test, we calculated the effect size using Cohen's d. Table V shows that Cohen's d value for the anthropomorphic preference score was 0.899. The standard error of Cohen's d was 0.130.

TABLE VI
REGRESSION COEFFICIENTS TABLE

Predictor	Unstandardized Coefficient	Standard Error	Standardized Coefficient	p-value
Interaction Style	-0.436	0.063	-0.374	$<$ .001
Age	-0.135	0.056	-0.135	0.015
Education	0.076	0.034	0.122	0.027

TABLE VII
REGRESSION MODEL SUMMARY TABLE

Metric	Value
R^2	0.209
Adjusted R^2	0.192
F-Statistic	12.239
p-value	$<$ .001

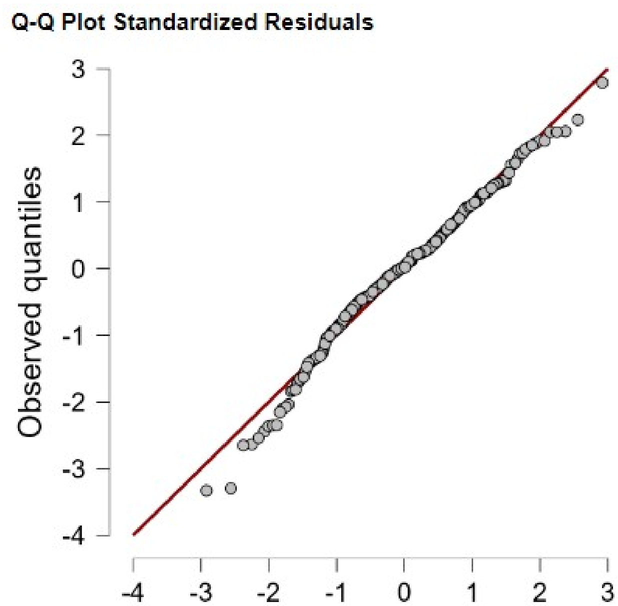

Fig. 1. Q-Q Plots standardized residuals

We performed a multiple regression analysis to investigate the influence of interaction styles and demographic variables on user acceptance. The adjusted R^2 value was 0.192 (F-statistic 12.239, $p < 0.001$), as shown in Table VII. Table VI shows that the interaction style had a p-value $<$ 0.001. Age and Education were significant predictors with a p-value of 0.015 and 0.027, respectively. Gender, Religion, and Profession had p-values $>$ 0.05. Figure 1 shows a Q-Q plot confirming that residuals followed a normal distribution.

V. Discussion

The study supports our hypothesis by evaluating the relationship between interaction styles and user acceptance. Welch's t-test provided a higher t-value of 6.887 which indicates that there is a statistically significant difference between the two independent groups where the anthropomorphic group has a higher mean score. The df of 141.685 was large indicating that the sample size was good, and the test was reliable. The extremely small p-value shows a high statistical significance. The probability that this result was obtained by chance is less likely ($<0.1\%$). The calculation of the effect size was performed using Cohen's d, which quantifies the effect size and provides insights into the practical significance of the results by determining the magnitude of the difference between the two groups. The value of Cohen's d was 0.899 and it is considered to be large if it is greater or equal to 0.8. This shows that the difference in mean preference score between anthropomorphic and non-anthropomorphic interaction style groups is noteworthy. The standard error of Cohen's d was 0.130 representing the precision of the estimated effect size. The combination of a significant t-test and a large Cohen's d value supports our hypothesis.

The multiple regression analysis determined that interaction style was the most significant predictor for user acceptance. The adjusted R^2 value of 0.192 indicates that the model significantly explained 19.2% of the variance in user acceptance. The anthropomorphic interaction style is associated with high user acceptance scores because the interaction styles had a p-value < 0.001. Among the demographic variables, age and education were also significant predictors where age negatively associated with user acceptance (p=0.015) inferring that older participants showed slightly lower preference and education positively associated with user acceptance (p=0.027) inferring that highly educated participants showed higher acceptance. Gender, Religion and Profession did not significantly influence user acceptance (p$>$ 0.05). The normal distribution of the Q-Q plot validated the assumption of the regression model.

VI. Conclusion

[Some placeholder text]

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