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From human to robot: A comparative analysis of agent bot anthropomorphic perceptions between Gen Y and Gen Z

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Abstract

This study investigates the significant differences between Generation Y and Generation Z in evaluating the perceived humanness or anthropomorphism of a designed chatbot and the effect of that evaluation on their intention to reuse it. Utilizing a scenario-based experiment and a survey, we examined the responses of 328 participants aged 17-39 years. Our analysis, employing independent sample t-tests and regression, revealed that Generation Y consistently rates the chatbot higher in virtual appearance, cognitive empathy, emotional empathy, moral virtue, and sociality compared to Generation Z. Additionally, cognitive empathy appears less influential in shaping reuse intentions as our designed bot failed to understand users' complex queries regarding promotional information and credit availability and calculations. The study also highlights the limitations of relying solely on static PDF-based knowledge, which restricts the chatbot's flexibility and depth in handling diverse queries .

Keywords: Anthropomorphic, Virtual Appearance, Morality, Cognitive, Emotional, Sociality

Abstrak

Penelitian ini menyelidiki perbedaan signifikan antara Generasi Y dan Generasi Z dalam mengevaluasi kesan manusiawi atau antropomorfisme dari chatbot yang dirancang serta pengaruh evaluasi tersebut terhadap niat mereka untuk menggunakannya kembali. Dengan menggunakan eksperimen berbasis skenario dan survei, kami memeriksa tanggapan dari 328 peserta berusia 17-39 tahun. Analisis kami, yang menggunakan uji t-sampel independen dan regresi, mengungkapkan bahwa Generasi Y secara konsisten menilai chatbot lebih tinggi dalam hal penampilan virtual, empati kognitif, empati emosional, kebajikan moral, dan sosialitas dibandingkan dengan Generasi Z. Selain itu, empati kognitif tampaknya kurang berpengaruh dalam membentuk niat penggunaan kembali karena chatbot yang kami rancang gagal memahami pertanyaan kompleks pengguna terkait informasi promosi serta ketersediaan dan perhitungan kredit. Studi ini juga menyoroti keterbatasan dari hanya mengandalkan pengetahuan berbasis PDF statis, yang membatasi fleksibilitas dan kedalaman chatbot dalam menangani berbagai pertanyaan.

Kata kunci: Antropomorfik, Penampilan Virtual, Moralitas, Kognitif, Emosional, Sosialitas

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Introduction

Over the past decade, marketing has undergone significant transformation driven by rapid technological advancements. Innovations in information technology, especially in Artificial Intelligence (AI), are creating exciting new opportunities for collaboration and value creation between businesses and consumers (Paschen et al., 2021; Singh et al., 2019). Now more than ever, companies must rethink how they interact with consumers and find new ways to differentiate themselves by offering superior customer experiences (Luo et al., 2019). AI plays a crucial role in delivering these enhanced experiences by enabling personalization through sophisticated data analysis (Chandra et al., 2022; Rafieian & Yoganarasimhan, 2023), providing instant 24/7 customer support via chatbots (Aslam, 2023; Cheng & Jiang, 2022; Kushwaha & Kar, 2024; Luo et al., 2019), utilizing predictive analytics to anticipate customer needs (Zulaikha et al., 2020), automating routine tasks for faster service (Aslam, 2023; Kumar et al., 2016; Stoilova, 2021), and enhancing interaction channels with voice assistants (Klaus & Zaichkowsky, 2020; Malodia et al., 2023) and augmented reality (Rauschnabel et al., 2022).

Fui-Hoon Nah et al. (2023) emphasized that the service industry is the sector most affected by advancements in AI technology, including generative AI. These technological innovations have driven remarkable progress in the service industry over recent years (Fernandes & Oliveira, 2021). For instance, the implementation of service robots, chatbots, and virtual assistants has become increasingly common in this sector (Gummerus et al., 2019). Chatbots are software applications designed to engage in natural language conversations with users (Sheehan et al., 2020). According Tintarev et al. (2016), these chatbots function as automated advisors, aiding users in decision-making processes. They interact with customers through voice or text, addressing various needs and inquiries (Crolic et al., 2022). Chatbots have become increasingly prevalent, serving as customer service agents on e-commerce platforms and personal voice-based assistants like Apple's Siri and Amazon's Echo (Go & Sundar, 2019; Johansson, 2021; Tuzovic & Paluch, 2018). Many individuals now use voice assistants in their daily lives, appreciating their utility, convenience, and meaningful interactions (McLean & Osei-Frimpong, 2019). As their underlying technology continues to advance, chatbots hold the potential to replace human service employees (Brandtzaeg & Følstad, 2018). Interestingly, while some experts argue that chatbots can enhance customer service, lower costs, and even satisfy a variety of user needs (Ameen et al., 2022; Chung et al., 2020; Edwards et al., 2014), others worry they might harm customer service quality and negatively affect businesses and satisfaction (Crolic et al., 2022; Hu & Sun, 2023).

Sheehan et al. (2020) describe that despite the widespread use of chatbots, they often fail to meet users' expectations due to miscommunication errors caused by their struggle to understand user input. For example, Facebook's Project M, a text-based virtual assistant, reportedly failed in over 70% of interactions, requiring human intervention to resolve the issues. Similarly, the shortcomings of two mental health chatbot apps for children, Wysa and Woebot, became alarmingly evident when they failed to recognize cases of sexual abuse (White, 2018). Air Canada's chatbots also disastrously provided incorrect discount information to a traveler, damaging the company's reputation (Yagoda, 2024). Ashfaq et al. (2020) argue that these incidents are a primary reason why user acceptance and the continuous intention to use chatbots remain relatively low. Hu and Sun (2023) further strengthened this argument by uncovering that a striking 87% of customers, according to a Forbes survey in 2019, prefer interacting with real human service representatives over chatbots.

Bilquise et al. (2022) and Radziwill and Benton (2017) point out that a significant concern, which has become a primary root cause of the low adoption level of chatbots, is their inability to interact with users in a human-like way. Instead of engaging in meaningful conversations, these bots often only provide basic (pragmatic quality) information to its users. Strengthening the hedonic quality of chatbots human likeness, such as their ability to engage and stimulate users, can greatly improve the user experience, thus enhances satisfaction level (Følstad & Brandtzaeg, 2020). Another critical barrier to chatbot adoption is technical limitations; chatbots frequently fail to understand user input correctly or provide accurate information. Savastano et al. (2024) pointed out that the most significant obstacles to adopting chatbots are the efforts required to minimize error rates and the substantial financial investment involved. When chatbots make errors, people are more likely to penalize them compared to human mistakes, which reduces their willingness to trust and rely on these algorithms over time (Dietvorst et al., 2015; Renier et al., 2021).

However, recent advancement technologies like OpenAI's ChatGPT and Meta's Llama have shown promising results in addressing these technical limitations. These platforms utilize advanced natural language processing and machine learning techniques to improve the accuracy and contextual understanding of chatbots. For example, ChatGPT's capability to generate high-quality, human-like responses to user inquiries has been a critical factor in its success. It has significantly enhanced the conversational performance of intelligent customer service systems, leading to increased user satisfaction and loyalty (Peres et al., 2023). Similarly, Meta's Llama models have proven highly effective in interacting with users, demonstrating human-like fluency and creativity, and providing flexible solutions for content moderation and financial planning (Roumeliotis et al., 2023).

This study aims to focuses on how users perceive the humanness (human-likeness) of chatbots. Schuetzler et al. (2020) state that the more chatbots act in human-like ways, the more people tend to attribute human traits to them and respond to their humanness by applying conversational norms. This phenomenon, where human characteristics, emotions, and intentions are attributed to chatbots, is also known as anthropomorphism. Anthropomorphism, originating from the Greek words anthropos (human) and morphe (form or structure), denotes the tendency to assign human characteristics to inanimate objects, animals, and other non-human entities, aiding in the rationalization of their actions (Epley et al., 2007). In the realm of machine-human interaction, perceived anthropomorphism is defined as the attribution of human-like features, motivations, intentions, emotions, and behaviors to non-human agents (Munnukka et al., 2022). Non-human agents exhibiting these qualities are perceived as anthropomorphic or human-like. Essentially, anthropomorphism can be described as the inclination to assign emotional states to non-living objects (Nijssen et al., 2021).

A previous study by Nass and Moon (2000) distinguished between two types of anthropomorphism, referred to as mindful and mindless anthropomorphism. Mindful anthropomorphism involves a conscious assessment of whether an interface, such as a chatbot, appears human-like or machine-like. Conversely, mindless anthropomorphism refers to the unconscious attribution of human characteristics, such as friendliness or sociability, to the interface (Kim & Sundar, 2012; Proudfoot, 2011). Seven year later, Epley et al. (2007) introduced the "SEEK" model (Sociality, Effectance, Elicited Knowledge) to explain factors influencing anthropomorphism. Elicited agent knowledge is the cognitive aspect, where people judge unfamiliar non-human objects based on their similarity to themselves or others they know, such as attributing friendly characteristics to a robot with a human-like face (Waytz et al., 2010). Sociality motivation refers to the desire for social connections, leading to increased anthropomorphism in situations of loneliness, like talking to a virtual assistant when feeling isolated. Effectance motivation is the need to understand and control one's environment, seen when people think a malfunctioning computer is "acting up on purpose" to make sense of its behavior (Blut et al., 2021). Additionally, Hu and Sun (2023) divide anthropomorphism into internal and external cues: internal cues include emotional empathy, such as a chatbot that understands emotions (Go & Sundar, 2019; Primanto & Rachma, 2023; Rhim et al., 2022), and cognitive empathy, like a virtual assistant anticipating needs (Suhaili et al., 2021), while external cues refer to a human-like virtual appearance (Go & Sundar, 2019). On the other hand, the notion of moral personhood emphasizes the significance of moral virtues in defining an individual. According to this view, to be acknowledged as an individual, one must demonstrate attributes such as kindness, trustworthiness, and a sense of honor, which collectively constitute moral virtue (Golossenko et al., 2020). This concept correlates with anthropomorphism in that when we attribute human-like characteristics to non-human entities, we often extend these moral virtues to them as well. By perceiving chatbots or robots as possessing kindness or trustworthiness, we are engaging in a form of anthropomorphism that not only enhances their human-like qualities but also influences how we interact with and accept these technologies.

This study uses five dimensions of anthropomorphism to measure the tendency of chatbot humanness: virtual appearance, cognitive empathy, emotional empathy, moral virtue, and sociality. To the best of the authors' knowledge, this is the first framework to utilize these five dimensions together. Furthermore, the study includes respondents from Indonesia, divided into two generational cohorts: Generation Y and Generation Z. Previous studies found that the effects of different age groups differ in factors such as perceived ease of use, perceived security, and the need for additional human contact (Belen Saglam et al., 2021; van der Goot & Pilgrim, 2019). Terblanche & Kidd (2022) added that age showed a moderation tendency on effort expectancy, indicating that different age groups may have varying tolerance levels for the effort required to use chatbots. By analyzing these generational differences, this study aims to provide a comprehensive understanding of how diverse user groups perceived humanness of chatbot. Finally, a query search on Google Scholar for the keywords "anthropomorphism", "chatbot", and "Indonesia" yielded very few results, indicating that research on this topic is still very rare.

H1: Generation Y and Generation Z significantly differ in their perception of chatbot humanness based on virtual appearance.

H2: There is a significant difference between Generation Y and Generation Z in how cognitive empathy influences their perception of chatbot humanness.

H3: Generation Y and Generation Z differ significantly in their perception of chatbot humanness based on emotional empathy.

H4: The impact of moral virtue on the perception of chatbot humanness varies significantly between Generation Y and Generation Z.

H5: There are significant differences between Generation Y and Generation Z in their perception of chatbot humanness based on sociality.

This study also aims to examine the influence of each dimension of anthropomorphism on the intention to reuse chatbots. Previous research found a positive correlation between perceived humanness or anthropomorphism and the intention to reuse chatbots (Lei et al., 2021; Moriuchi, 2021; Silva et al., 2023). In other words, the higher the level of anthropomorphism in a chatbot, the more likely users are to reuse it.

H6: There is a positive relationship between the virtual appearance of chatbots and users' intention to reuse the chatbot.

H7: There is a positive relationship between cognitive empathy in chatbots and users' intention to reuse the chatbot.

H8: There is a positive relationship between emotional empathy in chatbots and users' intention to reuse the chatbot.

H9: There is a positive relationship between the perceived moral virtue of chatbots and users' intention to reuse the chatbot.

H10: There is a positive relationship between the sociality of chatbots and users' intention to reuse the chatbot.

Method

To evaluate the research hypotheses of this study, a quantitative method was adopted, utilizing a scenario-based experiment and a survey. The experiment employed a Two-Group Posttest-Only Design, which is an experimental approach where two groups are exposed to controlled conditions, with measurements taken only after the treatments have been applied. This design is known for its simplicity and effectiveness in research (Hoecker, 2007).

The primary data collection was conducted online, allowing us to quickly gather a substantial amount of data and automate the process, which boosted response rates. We shared the online questionnaire mainly on social media platforms like WhatsApp. To reach more people, we used a non-random sampling method that included both convenience and snowball sampling techniques. Respondents were required to answer two demographic questions to confirm sampling criteria, two question about previous chatbot experiences, and 22 questions related to the actual chatbot interaction in the experiment.

This study employs a 2x1 factorial design, integrating both an experiment and a survey to compare two generational cohorts: Generation Y (born roughly between the mid-1980s and mid-1990s) and Generation Z (born after the mid-1990s). Chattaraman et al. (2019) highlight that the AI industry prioritizes younger generations due to their tendency to be early adopters and their greater inclination toward new technologies (Liébana-Cabanillas et al., 2014). Millennials are recognized as a technologically proficient group (Bilgihan, 2016) and are four times more likely than baby boomers to utilize virtual assistants (Tuzovic & Paluch, 2018). Generation Z, on the other hand, has been immersed in technology from a very young age, making them digital natives with a high level of comfort and familiarity with advanced technology. This cohort is characterized by its preference for seamless digital interactions and instant access to information. Studies have shown that Generation Z is highly engaged with social media platforms and digital communication tools, which shape their expectations for intuitive and interactive technological experiences (Turner, 2015).

In the experimental scenario, participants from both generations were assumed to be planning to purchase a motorcycle from a specific brand. They engaged in a conversation with our designed online customer service agent (the bot) to gather comprehensive information about the motorcycle, including color choices, engine specifications, pricing, and availability. The knowledge base of our bot was compiled in a PDF format, allowing the AI to retrieve answers from this documentation directly, delivering responses in both text and voice formats. Following the interaction, respondents completed a survey measuring their perceptions of the chatbot's human-like qualities and their intention to reuse the chatbot in the future. These human-like qualities, known as perceived humanness (Borau et al., 2021; Lu et al., 2022), were measured through five dimensions of anthropomorphism selected for this study: virtual appearance, cognitive empathy, emotional empathy, moral virtue, and sociality.

Virtual appearance (VAP) is defined as the assessment of how visually similar the bot is to a human, encompassing aspects such as interface design, avatar profile, and other visual elements that make the bot appear more human-like. To measure virtual appearance, three items were adopted from Golossenko et al. (2020) and Hu and Sun (2023). Respondents in this study used a 5-point Likert scale (ranging from 1=strongly disagree to 5=strongly agree) to rate their perception of the bot's virtual appearance. The measurement items of VAP in this study can be described as follows, "The avatar of the agent chat looks like a real person (VAP1)," "The avatar of the agent doesn't look like a robot (VAP2)," and "The avatar of the agent is life-like (VAP3)".

Cognitive empathy (COG) refers to the bot's ability to understand and respond to users' needs and thoughts. This dimension evaluates how effectively the bot can interpret and address users' questions or requests in a manner that demonstrates deep understanding. To measure cognitive empathy, four items with a 5-point Likert scale (ranged from 1=strongly disagree to 5=strongly agree) were adapted from Golossenko et al. (2020), Suhaili et al. (2021) and Hu and Sun (2023). The measurement items are: "The agent generates responses based on what we talk about (COG1)," "The agent can carefully analyze my needs (COG2)," "The agent effectively addresses my requests in a way that demonstrates understanding (COG3)," and "The agent is capable of reasoning (COG4)". Emotional empathy (EMO), on the other hand, relates to the bot's ability to recognize and respond to users' emotions. This includes the bot's reactions to the user's tone of voice or specific words indicating certain feelings, as well as its proficiency in expressing empathy through its responses. To assess emotional empathy, four items with a 5-point Likert scale (ranging from 1 = strongly disagree to 5 = strongly agree) were adapted from Golossenko et al. (2020) and Hu and Sun (2023). The items are: "The agent provides me with personalized recommendations (EMO1)," "The agent can interact with my emotions (EMO2)," "My communication with the agent is pleasant (EMO3)," and "The agent can experience shame when user have negative views about their explanations (EMO4)".

Moral virtue (MOR) refers to the moral attributes demonstrated by the bot, such as honesty, reliability, and respect. This dimension evaluates how well the bot can exhibit the ethical behavior expected from humans. To measure this variable, three items with a 5-point Likert scale (ranging from 1 = strongly disagree to 5 = strongly agree) were adapted from Golossenko et al. (2020). The items used in the study are: "The agent is trustworthy (MOR1)," "I feel that the agent is honest (MOR2)," and "The agent treats me with respect (MOR3)." In contrast, sociality (SOC) in this study was measured using two scales from Fernandes and Oliveira (2021) and Schuetzler et al. (2020), namely perceived social interactivity and perceived social presence. The items can be described as follows: "I find the agent pleasant to interact with (SOC1)," "I feel the agent understands me (SOC2)," "I feel a sense of warmth from the agent (SOC3)," and "The agent makes me feel comfortable during our interactions (SOC4)." Respondents rated these items on a scale from 1 (strongly disagree) to 5 (strongly agree).

Table 1. Demographic Profiles

Profiles	Frequency
Generation	
Y (29-39 years)	162
Z (17-28 years)	166
Gender	
Male	124
Female	204
Have you ever used a chatbot before?	
Yes	311
No	17
If you have used chatbot before, how was your experience?	
Good	276
Neutral	23
Bad	12

Source: Processed Data

Additionally, intention to reuse (INT), defined in this study as the tendency of users to reuse the chatbot in the future, was measured with a 5-point Likert scale using items adapted from previous studies (Lei et al., 2021; Silva et al., 2023). The items include: "If I want to buy a motorcycle, I will ask the chatbot first (INT1)," "I will consult the chatbot as much as possible whenever I want to buy a motorcycle (INT2)," "I plan to use this chatbot in the future whenever I'm looking for motorcycle information (INT3)," and "I will rely on this chatbot for future motorcycle purchases (INT4)."

A total of 328 respondents, aged 17-39 years old, participated in our study from April until May 2024, with a balanced distribution of 166 respondents classified as Generation Z and 162 as Generation Y. Gender distribution also showcases a well-rounded sample, with 124 males (38%) and 204 females (62%), providing insights into potential gender-based differences in interaction with chatbot technology. A significant majority of participants, 311 individuals (95%), reported having prior experience with chatbots. This high level of familiarity underscores the growing prevalence and acceptance of chatbot technology. Among those with prior chatbot experience, the overwhelming majority, 276 respondents (89%), rated their interactions as good, while only a small fraction had neutral (23 respondents, 7%) or bad (12 respondents, 4%) experiences. With 328 respondents, our sample size meets the minimum requirement as specified by Kline (2023), who mentioned that the minimum sample size should be at least 100 ($n \geq 100$ rule). The details of the demographics are provided in Table 1.

Furthermore, to assess the validity and reliability of the study, we used the Pearson correlation and Cronbach's alpha approach. A Pearson correlation coefficient with a significance level (p-value) of less than 0.05 was considered acceptable for establishing construct validity. For reliability, a Cronbach's alpha value of 0.60 or above was deemed acceptable, indicating a satisfactory level of internal consistency among the survey items. Table 2 presents the validity and reliability results for the variables and items utilized in this study.

The Intention to Reuse (INT) variable exhibits robust reliability with a Cronbach's alpha of 0.852, and its items (INT1 through INT4) demonstrate strong validity, with r-values ranging from 0.819 to 0.848, all significant at $p < 0.001$. The Virtual Appearance (VAP) variable shows moderate reliability with a Cronbach's alpha of 0.646, and its items (VAP1 through VAP3) have r-values between 0.606 and 0.837, all significant at $p < 0.001$. Cognitive Empathy (COG) has a reliability of 0.627, with items (COG1 through COG4) displaying r-values from 0.644 to 0.712, all significant at $p < 0.001$. Emotional Empathy (EMO) is measured with a reliability of 0.649, and its items (EMO1 through EMO4) show r-values

Table 2. Validity and Reliability Result

Variables/ Items	Validity		Reliability
	r-Values	Sig.	α
INT			0.852
INT1	0.819	<0.001	
INT2	0.827	<0.001	
INT3	0.835	<0.001	
INT4	0.848	<0.001	
VAP			0.646
VAP1	0.837	<0.001	
VAP2	0.832	<0.001	
VAP3	0.606	<0.001	
COG			0.627
COG1	0.702	<0.001	
COG2	0.712	<0.001	
COG3	0.689	<0.001	
COG4	0.644	<0.001	
EMO			0.649
EMO1	0.644	<0.001	
EMO2	0.720	<0.001	
EMO3	0.767	<0.001	
EMO4	0.655	<0.001	
MOR			0.762
MOR1	0.825	<0.001	
MOR2	0.807	<0.001	
MOR3	0.836	<0.001	
SOC			0.734
SOC1	0.837	<0.001	
SOC2	0.729	<0.001	
SOC3	0.695	<0.001	
SCO4	0.715	<0.001	

Source: Processed Data

ranging from 0.644 to 0.767, all significant at $p < 0.001$. The Moral Virtue (MOR) variable boasts high reliability at 0.762, with items (MOR1 through MOR3) exhibiting strong validity, indicated by r-values between 0.807 and 0.836, all significant at $p < 0.001$. Lastly, the Sociality (SOC) variable demonstrates good reliability with a Cronbach's alpha of 0.734, and its items (SOC1 through SOC4) show r-values from 0.695 to 0.837, all significant at $p < 0.001$.

Result

With the confirmation of validity and reliability for all variables and items, we moved forward with the data analysis. To evaluate the conceptual model and test our hypotheses, we employed a two-step analysis approach. First, we used an independent samples t-test to assess the differences in perceived anthropomorphism (INT, VAP, COG, EMO, MOR, and SOC) between Generation Y and Generation Z. Then, we conducted regression analysis to examine the impact of anthropomorphism dimensions (INT, VAP, COG, EMO, MOR, and SOC) on the intention to reuse the chatbot.

Table 3. Normality and Multicollinearity Result

Variables	Normality	Multicollinearity	
	Monte-Carlo (Sig.)	Tollerance	VIF
INT	0.622		
VAP	0.339	0.846	1.182
COG	0.686	0.724	1.381
EMO	0.460	0.783	1.278
MOR	0.432	0.684	1.462
SOC	0.654	0.899	1.112

Source: Processed Data

Table 3 presents the results for normality and multicollinearity tests, which are critical for ensuring the robustness of our analysis. The normality of the variables was assessed using the Monte-Carlo significance test, with a common threshold for normality being a significance value (p-value) greater than 0.05. The results indicate that all variables meet the normality assumption, with Monte-Carlo significance values as follows: INT (0.622), VAP (0.339), COG (0.686), EMO (0.460), MOR (0.432), and SOC (0.654). These values all exceed the 0.05 threshold, confirming that the data is normally distributed. Multicollinearity, on the other hand, was evaluated using Tolerance and Variance Inflation Factor (VIF) values. Accepted thresholds are Tolerance values greater than 0.1 and VIF values less than 10. The results show that VAP, COG, EMO, MOR, and SOC have Tolerance values of 0.846, 0.724, 0.783, 0.684, and 0.899, respectively, and VIF values of 1.182, 1.381, 1.278, 1.462, and 1.112, respectively. All these values fall within the acceptable limits, indicating no multicollinearity issues among the variables.

Table 4. Heteroscedasticity (Glejser) Result

Relationship	t-Values	Sig.
VAP -> ABS(RES)	1.900	0.058
COG -> ABS(RES)	1.101	0.272
EMO -> ABS(RES)	0.161	0.872
MOR -> ABS(RES)	2.395	0.171
SOC -> ABS(RES)	0.146	0.884

Source: Processed Data

Table 4 presents the results of the heteroscedasticity test using the Glejser method, which examines the relationship between the independent variables and the absolute values of the residuals (ABS(RES)). The significance level for determining the presence of heteroscedasticity is commonly set at $p < 0.05$. The relationship between Virtual Appearance (VAP) and ABS(RES) shows a t-value of 1.900 and a significance level of 0.058, which is slightly above the threshold, suggesting no significant evidence of heteroscedasticity for VAP. Cognitive Empathy (COG) has a t-value of 1.101 and a significance level of 0.272, well above the threshold, indicating no heteroscedasticity issues for this variable. Emotional Empathy (EMO) exhibits a t-value of 0.161 and a significance level of 0.872, confirming the absence of heteroscedasticity concerns. Moral Virtue (MOR) presents a t-value of 2.395 with a significance level of 0.171, which is also above the threshold, indicating no significant heteroscedasticity for this variable. Lastly, Sociality (SOC) shows a t-value of 0.146 and a significance level of 0.884, suggesting no heteroscedasticity concerns for SOC. In summary, the Glejser test results indicate that none of the variables exhibit significant heteroscedasticity, as all p-values are greater than 0.05. This implies that the assumption of homoscedasticity is met for the dataset, allowing for reliable regression analysis.

Table 5 presents a compelling analysis of independent sample t-test results, shedding light on the significant differences in perceptions of anthropomorphism between Generation Y and Generation Z. The results for Hypothesis H_1 reveal that the perceived virtual appearance (VAP) differs markedly between the two generations, as evidenced by a t-value of 6.060 and a significance level of less than 0.001, emphasizing the generational gap in how virtual appearances are perceived. Similarly, Hypothesis H_2 shows a significant divergence in cognitive empathy (COG), with a t-value of 8.343 and a p-value less than 0.001, highlighting the pronounced differences in how each generation processes and interprets cognitive empathy through chatbots. The analysis of Hypothesis H_3 uncovers a significant disparity in emotional empathy (EMO) perceptions, demonstrated by a t-value of 7.730 and a p-value below 0.001. Moral virtue (MOR) perceptions, as explored in Hypothesis H_4, shows a t-value of 24.880 and a significance level of less than 0.001, underscores the profound gap in moral virtue perceptions between the two generations. Lastly, Hypothesis H_5 highlights a notable difference in sociality (SOC), with a t-value of 3.453 and a p-value under 0.001. These results collectively underscore the significant differences in how Generation Y and Generation Z perceive various dimensions of anthropomorphism.

Table 6 presents the regression results for hypotheses H_6 through H_{10}, examining the influence of various dimensions of anthropomorphism on the intention to reuse the chatbot (INT). Virtual appearance (VAP) shows a positive relationship with intention to reuse, indicated by a beta coefficient of 0.232, a t-value of 2.628, and a significance level of 0.009, confirming its statistical significance.

Emotional empathy (EMO) similarly exhibits a significant positive relationship, with a beta coefficient of 0.213, a t-value of 2.669, and a significance level of 0.008. Moral virtue (MOR) demonstrates the strongest positive impact, with a beta coefficient of 0.444, a t-value of 6.274, and a highly significant p-value of less than 0.001. Sociality (SOC) also has a significant positive effect, shown by a beta coefficient of 0.160, a t-value of 2.303, and a significance level of 0.022. However, cognitive empathy (COG) does not significantly influence the intention to reuse the chatbot, as indicated by its beta coefficient of 0.337, a t-value of 0.666, and a non-significant p-value of 0.886.

Table 5. Independent Sample t-Test Result

Hypotheses	t-Test	
	t-Values	Sig.
H_1, **Accepted**		
VAP_GENY≠VAP_GENZ	6.060	<0.001
H_2, **Accepted**		
COG_GENY≠COG_GENZ	8.343	<0.001
H_3, **Accepted**		
EMO_GENY≠EMO_GENZ	7.730	<0.001
H_4, **Accepted**		
MOR_GENY≠MOR_GENZ	24.880	<0.001
H_5, **Accepted**		
SOC_GENY≠SOC_GENZ	3.453	<0.001

Source: Processed Data

Table 6. Regression Result

Hypotheses	β	t-Values	Sig.
H_6 VAP -> INT	0.232	2.628	0.009
H_7 COG -> INT	0.337	0.666	0.886
H_8 EMO -> INT	0.213	2.669	0.008
H_9 MOR -> INT	0.444	6.274	<0.001
H_{10} SOC -> INT	0.160	2.303	0.022

Source: Processed Data

Table 6 presents the regression results for hypotheses H_6 through H_{10}, examining the influence of various dimensions of anthropomorphism on the intention to reuse the chatbot (INT). Virtual appearance (VAP) shows a positive relationship with intention to reuse, indicated by a beta coefficient of 0.232, a t-value of 2.628, and a significance level of 0.009, confirming its statistical significance. Emotional empathy (EMO) similarly exhibits a significant positive relationship, with a beta coefficient of 0.213, a t-value of 2.669, and a significance level of 0.008. Moral virtue (MOR) demonstrates the strongest positive impact, with a beta coefficient of 0.444, a t-value of 6.274, and a highly significant p-value of less than 0.001. Sociality (SOC) also has a significant positive effect, shown by a beta coefficient of 0.160, a t-value of 2.303, and a significance level of 0.022. However, cognitive empathy (COG) does not significantly influence the intention to reuse the chatbot, as indicated by its beta coefficient of 0.337, a t-value of 0.666, and a non-significant p-value of 0.886.

Discussion

This study discovered a significant difference between Generation Y and Generation Z in evaluating the perceived humanness or anthropomorphism of our designed chatbot (Belen Saglam et al., 2021; Terblanche & Kidd, 2022; van der Goot & Pilgrim, 2019). Generation Y consistently gave higher ratings to the chatbot across all dimensions, including virtual appearance, cognitive empathy, emotional empathy, moral virtue, and sociality, compared to Generation Z. The starkest contrast was observed in the dimension of moral virtue, where Generation Y perceived the chatbot as significantly more honest, trustworthy, and respectful. Interestingly, despite Generation Z's strong interest in advanced AI technology (Mason et al., 2022) and their reputation as the most adaptive generation to AI (Al-Sharafi et al., 2023), their deep understanding of AI (Chan & Lee, 2023) appears to fuel their concerns about the potential dangers of AI.

Vinichenko et al. (2022) supports this view, highlighting that Gen Z is cautious about AI, believing it poses risks to humans and should not be fully trusted in all aspects. This wariness likely influences their more critical evaluation of the chatbot's anthropomorphic qualities.

Interestingly, the results of this study also found that cognitive empathy appears less impactful in shaping chatbot reuse intention. Cognitive empathy itself can be defined as the bot's ability to understand and respond to users' needs and thoughts. Despite its theoretical importance, the findings suggest that users may not perceive cognitive empathy as a critical factor when deciding whether to reuse a chatbot. Unlike human agents, chatbots may struggle to convincingly interpret and address complex user needs and thoughts (Chaves & Gerosa, 2019; Kvale et al., 2019). For example, during the data collection process, some respondents informally mentioned that the voice assistant robot designed by the authors offered many new features and was very helpful for users who preferred quick interactions over prolonged text messaging. However, when some users asked for information related to ongoing promotions, credit availability and scheme calculations, service schedules, and nearby dealerships, the bot seemed confused and provided ambiguous and unclear responses.

The emergence of ambiguous and unclear responses can also be attributed to the design of the bot, which relies solely on knowledge documented and annotated in PDF format. This reliance is believed to cause a lack of flexibility in the bot's cognitive knowledge. Following Jacob et al. (2024) workflow for chatbots using Langchain-AI for PDF files, our designed bot operates by having users initially annotate important sections of PDFs, store specific queries, and create bookmarks for quick reference. These annotated and bookmarked PDFs are then stored in a database, where LangChain processes and indexes the information. By integrating semantic search capabilities driven by the latest Transformer language models, the system can understand and interpret the meaning behind user queries, surpassing traditional keyword-based methods. Users input natural language queries through a chat interface, which the semantic search engine processes to retrieve the most relevant sections of the PDFs. The results are then filtered, ranked, and presented in an organized manner, allowing users to interact further with the retrieved information.

The reliance on PDFs as the sole knowledge base introduces several limitations that contribute to static responses. Firstly, the static nature of PDF content means that the bot can only access pre-written and annotated information, lacking the ability to dynamically update or adapt its knowledge based on new information or evolving user needs. This rigidity results in the bot's inability to handle queries that fall outside the scope of the pre-annotated knowledge, leading to ambiguous and sometimes irrelevant responses. Additionally, PDF documents, by their very format, are not designed for interactive data retrieval, which can limit the depth and richness of the responses the bot can provide. Unlike databases that can be continually updated and queried in complex ways, PDFs offer a fixed set of information, which can hinder the bot's performance in delivering nuanced and contextually appropriate answers. To address these limitations, developers should focus on refining the algorithms that enable chatbots to better understand and process complex user inputs, ensuring that the responses are not only rapid but also accurate and relevant. By enhancing the bot's cognitive awareness, it can undertake complex tasks more dynamically (Spinelli & Basharat, 2011). Future bots should have the capability to access multiple databases simultaneously, making their responses more relevant and comprehensive for users.

The theoretical implications of this study are substantial for advancing management theory in the context of AI and human-chatbot interaction. First, the significant generational differences in chatbot evaluation highlight the need for personalized AI solutions tailored to the distinct values and perceptions of different age groups (Chandra et al., 2022; Rafieian & Yoganarasimhan, 2023). This aligns with the theory of consumer behavior segmentation, suggesting that generational cohorts may require unique engagement strategies to maximize user satisfaction and loyalty. Furthermore, the study's findings on moral virtue emphasize the importance of ethical AI design, reinforcing theories that advocate for trust and transparency as critical factors in technology adoption. Moreover, the emphasis on emotional empathy, virtual appearance, and sociality supports the human-chatbot interaction theory, which posits that human-like traits significantly influence user engagement.

Finally, this study effectively demonstrates the significant impact of virtual appearance, emotional empathy, moral virtue, and sociality on the intention to reuse chatbots (Golossenko et al., 2020; Hu & Sun, 2023; Lei et al., 2021; Moriuchi, 2021; Silva et al., 2023). The results indicate that as these qualities in a chatbot increase, so does the likelihood of users re-engaging with it. A visually appealing design can immediately captivate users, encouraging initial and repeated interactions. Emotional empathy, by providing personalized and gratifying exchanges, enhances user satisfaction and promotes continued use. Moreover, chatbots that embody moral virtues like honesty and reliability build trust, further encouraging users to return. Additionally, the ability of chatbots to participate in socially meaningful conversations enriches the user experience, making them more engaging and increasing the chances of future interactions.

Conclusion

This study reveals significant differences between Generation Y and Generation Z in evaluating the perceived humanness or anthropomorphism of a designed chatbot. Generation Y consistently rated the chatbot higher in virtual appearance, cognitive empathy, emotional empathy, moral virtue, and sociality compared to Generation Z. The most pronounced difference was observed in the dimension of moral virtue, indicating that Generation Y perceives the chatbot as significantly more honest, trustworthy, and respectful. Despite Generation Z's keen interest in advanced AI technology and their adaptability to AI, their deep understanding of AI leads to concerns about its potential dangers, affecting their evaluation of the chatbot. Furthermore, the study found that cognitive empathy appears less impactful in shaping chatbot reuse intention. Users may not perceive the bot's ability to understand and respond to needs and thoughts as crucial, particularly when the bot struggles with complex queries, leading to ambiguous responses. This limitation is exacerbated by the bot's reliance on static PDF-based knowledge, which hinders its flexibility and depth in responding to user queries. Thus, developers need to enhance chatbot algorithms to improve understanding and processing of complex inputs, ensuring responses are accurate and relevant. Finally, the study confirms the significant impact of virtual appearance, emotional empathy, moral virtue, and sociality on the intention to reuse chatbots, emphasizing the importance of integrating these human-like traits into chatbot design to foster user satisfaction and loyalty.

The study has several limitations. Firstly, it focuses only on Generation Y and Generation Z, potentially missing how other age groups perceive chatbots. Additionally, the chatbot's reliance on static PDF-based knowledge limits its ability to respond flexibly and deeply to complex queries, affecting its perceived cognitive empathy and overall effectiveness. The sample size and diversity might also be limited, making it hard to apply the results to a broader population. Lastly, the study's findings might be specific to certain situations and could vary in different contexts.

Future research should explore the integration of dynamic databases and real-time data sources to enhance chatbot flexibility and relevance. Investigating advanced natural language processing techniques can improve chatbots' ability to interpret and respond to complex queries more effectively. Additionally, examining the role of continuous learning algorithms in enabling chatbots to adapt to evolving user needs could provide valuable insights. Comparative studies involving other generational cohorts or demographic groups may help generalize the findings and uncover broader trends in chatbot usage. Finally, exploring the ethical implications and user trust dynamics in AI interactions can provide a deeper understanding of how to design chatbots that are not only effective but also widely accepted and trusted by diverse user groups.

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