Bits and Biases: Exploring Perceptions in Human-like AI Interactions Using the Stereotype Content Model

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Abstract: In an AI-infused world, user trust in responses generated by autonomous systems is of critical importance. Building upon the work of Ahn, Kim, and Sung (2022), this study examines the impact of stereotypes attributed to chatbots on user trust using the Stereotype Content Model (SCM), which relies on dimensions like warmth and competence for universal cross-culture social judgment. This research investigates how age-related stereotypes influence user perceptions of anthropomorphic AI, specifically chatbots, and their perceived warmth and competence. We conducted two experiments: Study 1 used AI-generated illustrations to present "young" and "old" chatbot personas, while Study 2 used realistic photos. Participants watched pre-recorded interactions with the chatbot "Dave" and evaluated its warmth and competence on a 9-point Likert scale. Data were collected through Prolific, ensuring a diverse sample. Study 1 found no significant differences in perceptions of warmth and competence between the young and old chatbot personas. However, Study 2 revealed that the younger persona was perceived as warmer than the older one, indicating that the realism of the chatbot's appearance affects stereotype activation. These results underscore the importance of aligning chatbot personas with user expectations to enhance trust and satisfaction.

1 INTRODUCTION

Artificial Intelligence (AI) language models are the most recent “hype” in technology. New models and generative AI are “born” every day, and AI usage has become almost ubiquitous. However, its acceptance may depend on how trustful (Choung, David, and Ross, 2023) and friendly it is considered to be (Tay, Jung, and Park, 2014) and its “human likeness” (Kim, Kang, and Bae, 2022).

To facilitate this interaction and improve AI’s trustfulness, research suggests that anthropomorphism (i.e. applying human characteristics to inanimate objects) can make human-AI agent interactions more familiar—nonetheless, guided by the same norms governing interpersonal relationships. (Aggarwal and McGill, 2012; Ahn, Kim, and Sung, 2022; Sreejesh and Anusree, 2017)

Hence, like human interactions, these relationships are also influenced by how we perceive and evaluate others’ “personality” traits (Ahn, Kim, and Sung, 2022). Since people interact with anthropomorphic robots and computers as if they were real humans (Nass et al., 1995; Nass, Steuer, and Tauber, 1994), various social traits, gender, and personality are important for interpersonal relationships, affecting relationships and evoking social stereotypes (Tay, Jung, and Park, 2014).

Though most studies regarding AI and stereotypes are focused on biases that appear in the agent responses, a few scholars have studied how these stereotypes may affect the trust in AI agent’s responses. The study of Ahn, Kim and Sung (2022) is an example; it explores the effects of gender stereotypes on evaluating AI recommendations, using the Stereotype Content Model (SCM) of Fiske, Cuddy and Glick (2007) which relies on dimensions like warmth and competence for universal cross-culture social judgment (Fiske, 2017; Fiske, Cuddy, and Glick, 2007). Others like Liu et al. (2022) have used the same scale applied to brands (Kervyn, Fiske, and Malone, 2022) and different anthropomorphic representations (El Hedhli et al., 2023).

Despite their interesting findings, the authors acknowledge the need for more research using other types of stereotypes, such as age, religion, social

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status, etc., and cross-cultural versions (Ahn, Kim, and Sung, 2022). Building on this, we conducted experiments focusing on age as the stereotype to be elicited..

This paper is structured in 6 sections: Section 2 offers a brief theoretical background on AI and human interaction and a deeper one on the concept of the "Computers Are Social Actors (CASA)" paradigm, as well as the Stereotype Content Model—the scale used to measure the expected results. In Section 3 and its subsections, we explain the experiments used and discuss the findings. Section 4 comprises conclusions and a brief general discussion; sections 5 and 6, address implications followed by limitations and future research suggestions.

2 THEORETICAL FRAMEWORK

AI technology is reshaping the service industry, creating new service experiences with substantial implications for both customers and managers (Doorn et al., 2017) and to make these human-machine interactions more familiar and easier, companies and developers use anthropomorphism (applying human characteristics to inanimate objects) (Aggarwal and McGill, 2012; Ahn, Kim, and Sung, 2022; Sreejesh and Anusree, 2017).

Individuals tend to attribute human-like qualities to entities that exhibit distinct human traits, like smiling expressions (Epley, Waytz, and Cacioppo, 2007). Prior research has highlighted the effectiveness of specific cues in conferring human-like attributes on inanimate objects and social agents. Notably, characteristics like human-like physical forms, perceived animacy, and interactivity induce anthropomorphism in objects (El Hedhli et al., 2023).

Researchers on human-machine interaction like Nass, Steuer and Tauber (1994) and Nass et. al (1995) have discovered that people interact with anthromorphic robotic/machine entities as if they were human, resembling regular human-human interactions; therefore, proposing a paradigm called CASA—Computers Are Social Actors.

The CASA paradigm avers that people will infer computers' "personalities" through cues received during interactions and will respond to these personalities as if they were human interactions (Nass et al., 1995). Accordingly, the CASA paradigm is often used to understand how people perceive AI in the context of human-computer interaction (Hong, Choi, and Williams, 2020). More recently, De Kervenoael et al. (2024) reinforced the CASA paradigm when interacting with service robots in retail environments, meaning that the concept still applies to human-computer interactions.

CASA studies consider human-human interactions and expect similar results when replicating them in a human-computer interaction (Edwards et al., 2019). Hence, the present study focuses on experimenting with human age-related stereotypes and technology knowledge in a chatbot interaction, as it would occur in a common human-human interaction.

Considering these similarities with human-human interactions, we propose to use the Stereotype Content Model (Fiske et al., 2002; Fiske, Cuddy, and Glick, 2007; Fiske, 2017; Kervyn, Fiske, and Malone, 2022) to assess how people evaluate machine entities regarding prejudices and social groups.

The Stereotype Content Model (SCM) posits that the stereotypes are encapsulated by two fundamental dimensions: warmth and competence (Fiske et al., 2002; Fiske, Cuddy, and Glick, 2007; Cuddy et al., 2009).

When individuals interact with someone for the first time, they instinctively assess whether the person exhibits benevolent and cooperative intentions, reflecting qualities associated with warmth. These qualities encompass traits like honesty, friendliness, and sincerity. Concurrently, they evaluate the person's capacity to translate these intentions into action, marking competence—characterized by attributes like knowledge, creativity, and efficiency (Cuddy, Glick, and Beninger ,2011; El Hedhli et al., 2023).

Thus, warmth signifies how individuals perceive others' intentions. When someone is perceived as well-intentioned, they are generally considered trustworthy; in contrast, competence pertains to an individual's ability to actualize their intentions.

Despite some concerns expressed by Friehs et al. (2022), the SCM has been used as a validated scale in various stereotype studies, regarding humans, and brands (Kervyn, Fiske, and Malone, 2022; Fournier and Alvarez, 2012; Liu et al., 2022), artificial intelligence (Kim, Kang, and Bae, 2022; Ahn, Kim, and Sung, 2022), robots (Tay, Jung, and Park, 2014) and even virtual influencers (El Hedhli et al., 2023).

Fiske et al. (2002) explicitly report in SCM studies about the age stereotype, especially related to older people being considered as having lower perceived competence and higher warmth. Thus, the main contribution brought by this article is integrate SCM and CASA, using experimental design studies to assess how people evaluate their dimensions of warmth and competence when interacting with different chatbot personas (younger vs. older).

We hypothesize that chatbot's persona (young vs. old) has a more positive impact on warmth when

older and a more positive impact on competence perception when younger. Accordingly, younger chatbot personas will enhance the perception of competence while simultaneously diminishing perceptions of warmth. On the other hand, at least regarding technology, older AI personas are evaluated as being warmer but presenting less competence than the younger ones.)

3 OVERVIEW OF STUDIES

In our research, we designed two experiments (Study 1 and Study 2) to assess the influence of the age of AI personas on their evaluation, grounded in the SCM framework (Fiske, Cuddy, and Glick, 2007). In these studies, we intend to systematically vary AI personas' age cues to assess their respective impacts on the perceived dimensions of warmth and competence.

The study was designed by requesting participants to evaluate a pre-recorded interaction between a chatbot named "Dave" and a user seeking recommendations for purchasing a new wireless mouse. We chose the wireless mouse product based on previous studies where the product was found to be relevant but utilitarian, lacking significant emotional involvement or hedonic features (Ahn, Kim, and Sung, 2022). To provide hints about the chatbot's personality, we used AI-generated images. All chatbots presented in the pre-recorded interactions were referred to simply as "Dave." Other chatbot characteristics, such as the text used, remained identical for all interactions.

In both studies, participants were randomly directed to one of the interactions (young vs. old) and responded to six questions related to the SCM using a 9-point Likert scale, attention checks, and manipulation checks. Additionally, some questions related to participant profiles, such as age and gender, were included.

3.1 Study 1

In this study, we aimed to identify the impacts on the "warmth" and "competence" dimensions resulting from variations in the age of the persona adopted by the chatbot.

Using the Prolific platform, we collected 203 observations, one of which did not pass the attention check ("What was the name of the chatbot on the interaction you just saw?"). This was excluded from the study, leaving 202 valid observations, which were divided into 100 in the "Young Dave" condition (watching the interaction with the young chatbot) and 102 in the "Old Dave" condition (watching the interaction with the old chatbot). Figure 1 shows the pictures used to represent the chatbot's persona in the first experiment.

Besides seeking confirmation of the chatbot's name (Dave), we created a manipulation check, in which the participant had to evaluate the chatbot's age. Participants rated Old Dave's age as 59 on average (Std. Deviation = 19,8) and Young Dave's age as 28 on average (Std. Deviation = 13,5). Therefore, we considered all 202 observations as valid. Female participants comprised 60% of the sample and male participants 40% (one participant did not disclose gender), all of them declaring English to be their main language. The average age of the participants was 37,1 years—37,7 for female participants and 36,3 for males.

Figure 1: Illustrations used as stimuli to impersonate Old/Young Dave chatbot in study 1.

Preliminary analysis using SPSS indicated that the questionnaire related to the SCM demonstrated satisfactory validity (COMPETENCE Cronbach's Alpha = 0.914 / WARMTH Cronbach's Alpha = 0,910), confirming the scale's applicability.

3.2 Results

We conducted a MANOVA to identify significant differences in the means of the "warmth" and "competence" dimensions among participants assigned to each of the conditions of AI_PERSONA (Old Dave and Young Dave). The multivariate analysis did not reveal any significant differences in the perceptions of these two dimensions.

Contrary to previous work on SCM and CASA, it seems—at least relating to illustration-like chatbot personas—that age stereotypes are not elicited. Therefore, our main hypothesis, that the "older" Dave chatbot would elicit the elderly people stereotype (being warmer and less competent than "young" Dave) was not supported. Due to the non-significant differences in the previous study, we redesigned the experiment using more realistic photos, instead of illustrations – as the use of illustration-like stimuli could interfere with the perceived anthropomorphism level.

Table 1: Descriptive Statistics and MANOVA results for study 1 – (Young Dave vs Old Dave).

Dependent Variable	df	F	Sig.	Chatbot Persona	Means	Std. Deviation	N
COMPETENCE	1	0,113	0,737	Old Dave	6,4854	1,71992	103
				Young Dave	6,5657	1,66834	99
WARMTH	1	0,064	0,8	Old Dave	6,0065	1,88272	103
				Young Dave	5,9394	1,88283	99

3.3 Study 2

Due to our results and considerations on Study 1, we replicated the same experiment, with the same pre-recorded interaction, but with more realistic anthropomorphism (Figure 2) instead of illustration-like pictures. Like the previous experiment, the following images were AI generated.

Figure 2: More realistic pictures used as stimuli to impersonate Real Old/Young Dave chatbot in Study 2.

Using Prolific again, we collected 206 completed questionnaires. Four respondents did not pass the attention check ("What was the name of the chatbot on the interaction you just saw?") and were excluded, leaving 202 valid observations: 100 in the "Young Dave" condition (watching the interaction with the young chatbot) and 102 in the "Old Dave" condition (watching the interaction with the old chatbot). Female participants constituted 60,8% and male participants (two participants identified as non-binary) 39,1%, all of whom declared that English was their primary language. The average age of the participants was 38,2 — 38,0 for female participants and 38,9 for males.

Besides seeking confirmation of the chatbot's name (Dave) as an attention check, we also conducted a manipulation check, in which the participant had to evaluate the chatbot's age (N=200). Participants rated Old Dave's age as 44,8 on average (N=100; Std. Deviation = 16,0) and Young Dave's age as 27,2 on average (N=100; Std. Deviation = 11,3).

3.4 Results

Again, after verifying SCM scale validity (COMPETENCE Cronbach's Alpha = 0.883 / WARMTH Cronbach's Alpha = 0,904), we conducted a MANOVA to identify significant differences in the means of the "warmth" and "competence" dimensions among respondents assigned to each of the conditions of chatbot's persona (Old Dave vs. Young Dave).

Table 2: Descriptive Statistics and MANOVA results for study 2 – young/old with more realistic images.

Dependent Variable	df	F	Sig.	Chatbot Persona	Means	Std. Deviation	N
COMPETENCE	1	3,034	0,083	Old Dave	6,2680	1,82938	102
				Young Dave	6,6800	1,51455	100
WARMTH	1	5,046	0,026	Old Dave	5,6340	2,06789	102
				Young Dave	6,2000	1,45412	100

In accordance with our initial analysis and understanding, more realistic representations used as stimuli were in fact able to create differences in respondents' perceptions. However, while we expected the older persona to be rated warmer, the REAL YOUNG DAVE was rated warmer than the REAL OLD DAVE instead (OLD DAVE = 5,6340; YOUNG DAVE = 6,1961).

Since the average estimated age of REAL OLD DAVE was 45, we postulate that the perceived age was not significant enough to characterize the picture as "elderly". Therefore, the associated prejudices did not arise.

4 CONCLUSIONS

Our research explores the impact of age-related variations in a chatbot's persona on the two fundamental dimensions of "warmth" and "competence." In two separate studies, we presented participants with interactions featuring a chatbot named "Dave" portrayed as young and older individuals.

However, a preliminary analysis in the first study did not reveal any significant differences in the perceptions of these dimensions between the two age groups. This outcome suggests that the abstract and less anthropomorphic nature of illustrations might have hindered the activation of age-related stereotypes. The result goes against previous SCM and CASA research, implying that at least when experimenting with illustration-like AI generated images as chatbot's personas age stereotypes are not elicited. Consequently, considering these results and theoretical base, we conducted a follow-up experiment replacing the illustrations with more realistic photos to better understand whether the persona's realism would influence the participants' judgments. In contrast, in the second experiment, the more realistic stimuli had effect on perceptions – highlighting how more lifelike depictions may prompt stronger stereotype-related judgments.

However, contrary to the hypothesized outcome that the older persona would exhibit higher warmth, the younger persona was rated warmer, likely because the perceived age of the older persona was insufficient to evoke elderly-related biases. These findings highlight the importance of ensuring that stimuli used in stereotype studies effectively convey the intended traits, since prior research suggests that stereotype activation depends on clear and pronounced cues (Fiske, 2017).

5 MANAGERIAL IMPLICATIONS

On a theoretical level, our study contributes to the ongoing discourse surrounding human-AI interactions by shedding light on the complex interplay between anthropomorphism, stereotypes, and user perceptions.

By exploring the impact of age stereotypes on evaluations of chatbot personas, we extend existing research on the "computers are social actors" paradigm, demonstrating its relevance in contemporary AI applications. Moreover, our findings raise questions about the role of stereotypes in shaping user behaviors in and evaluations of human-AI interactions.

Partially reinforcing the principles outlined in the "computers are social actors" paradigm (Nass et al., 1995), our study offers insights and questions for managers considering the deployment of or already having chatbots deployed for customer service – where chatbots are seen as a promising technology for service providers (Nicolescu & Tudorache, 2022). It is necessary to seriously research and study which "persona" or personality to attribute to chatbots because they directly influence the perceptions consumers derive from their interactions (Lian & Lian, 2023). Choosing the appropriate persona for chatbots becomes relevant as it directly influences consumers' perceptions of warmth and competence, which in turn affect their trust (Choung et al., 2023) and satisfaction levels (Hsu & Lin, 2023). Thus, we emphasize the importance of matching chatbot personas with user expectations to optimize trust and engagement, a critical insight for digital customer service managers seeking to enhance user satisfaction and the effectiveness of their channels.

6 LIMITATIONS

Despite its limitations, our study contributes to the dynamics of human-AI interactions, particularly regarding the implications of anthropomorphism and stereotypes on user perceptions. While the use of pre-recorded interactions in this study offers a controlled environment for assessing respondents' perceptions, it lacks the complexity of real-world interactions. Future research could benefit from incorporating live interactions between participants and AI systems to capture the dynamic nature of human-AI interactions more accurately. By doing so, researchers could observe how perceptions of warmth and competence evolve over the course of a conversation, providing insights into the sustained impact of anthropomorphism and stereotypes in longer interactions.

Moreover, the study's focus on a single utilitarian product (wireless mouse) limits the generalizability of its findings to other contexts and how different personas may have different evaluations according to the subject of interaction. To address this limitation, future research could explore interactions with a broader range of products, including those with varying levels of emotional involvement or hedonic features.

Furthermore, while the study examines age stereotypes, there is a notable absence of exploration into other types of stereotypes that may influence perceptions of chatbot personas. Future research could expand upon this by investigating how stereotypes related to gender, ethnicity, socio-economic status, or technological expertise impact users' willingness to accept suggestions and engage with AI systems. By examining a wider array of stereotypes, researchers can gain a more comprehensive understanding of the factors that shape users' perceptions and behaviors in human-AI interactions.

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