When Shape Sells: How Chatbot Body Size and Long-Term Orientation Shape Consumer Responses Across Search vs. Credence Purchase Contexts

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Abstract

This research examines how a chatbot's body size affects consumer responses to search versus credence goods. Using the Stereotype Content Model and Social Perception Theory, we suggest that thin chatbots signifying competence match credence goods, whilst heavy chatbots signaling warmth match search goods. The body-based cues are particularly critical to low-long-term-oriented consumers, who show increased performance expectancy and lower effort for thin–credence and heavy–search matches. Conversely, high-long-term-oriented consumers focus on the chatbot's lasting technological value and show no differences across conditions. It indicates that temporal mindset determines whether users rely on immediate visual cues or future-oriented evaluations when assessing AI assistants.

Keywords: *Chatbot Body Size, Product Type***,** *Long-Term Orientation.*

Track: *Consumer Behavior*

1. Introduction

Chatbots are machine conversation systems that use natural language to interact with users (Hill et al., 2015). Their use across sectors to improve customer experience is widespread (Jiang et al., 2025). Recent research highlights chatbot features shape user responses, where chatbots' cuteness and emotional ability can boost expected service quality and usage intention (Wang et al., 2024); conversational styles that resemble those of humans can increase participants' willingness to share information with the chatbot (Chen et al., 2024); informal language styles can lead to increases in continuance intention and brand attitude (Li & Wang, 2023); while consistent anthropomorphic visuals and verbal delivery can serve to enhance emotional preference (Chen et al., 2025). However, no previous studies have attempted to investigate the influence on customer perceptions in sales consultation contexts regarding the body size of chatbots, presented as thin or heavy.

This work aims to analyse the impact of body size of chatbot's appearance on effectiveness in aiding consumers with search goods versus credence goods. Search goods have observable features that consumers can perform a priori comparison on before a purchase, which will lead to extensive information searching (Huang et al., 2009). Credence goods, on the other hand, are characterised by aspects which cannot be confirmed even after purchase, and therefore they generate uncertainty (Keeling et al., 2010). We suggest that thin chatbots that convey competence, expertise and analytical prowess are more appropriately targeted to credence goods that need expert-like, cognitive-directed guidance. Heavy chatbots (the kind that appear warm, friendly, supportive) are suitable for search goods in which consumers require assistance in finding and comparing information on the horizon. These congruent pairings (thin–credence; heavy–search) strengthen perceived compatibility of chatbot characteristics with task demands, enhancing performance expectancy while decreasing effort expectancy. We further examine long-term orientation (LTO) as a moderator. LTO, which captures forward-looking, perseverance-centered thinking (Hofstede & Bond, 1988), differs from short-term orientation; while short-term orientation accounts for short-term gain and lower adaptability (Ganguly et al., 2010). Low-LTO consumers rely on surface cues and respond more strongly to congruent chatbot–product matches. High-LTO consumers focus on long-term technological value, consistent with evidence that they prioritize future benefits in digital interfaces (Jung et al., 2020), yielding no differences across conditions.

2. Theoretical Foundation & Hypotheses Development

2.1 Social Perception Theory and Stereotype Content Model

Social Perception Theory (SPT) explains how people encode and interpret information about others (Grewal et al., 2020), relying on cues such as physical appearance (Krille et al., 2012) and body size (Bryksina et al., 2020) to infer traits (Malloy & Albright, 1990). Even slight deviations in body size shape judgments (Bryksina et al., 2020). This aligns with the Stereotype Content Model (SCM), which posits that social perceptions map onto warmth and competence (Cassiano et al., 2022). Warmth reflects sincerity and friendliness, whereas competence involves intelligence and efficiency (Yao et al., 2024). Integrating SPT and SCM offers a robust framework for understanding how chatbot body size shapes consumer perceptions across product types.

2.2 Congruency between a thin chatbot with search goods and a heavy chatbot with credence goods

Drawing on the Stereotype Content Model and Social Perception Theory, consumers use body-size cues to infer a chatbot's qualities (Fiske et al., 2002; Carter & McCullough, 2013). Heavy chatbots are perceived as warm, friendly, and socially supportive, making them effective for search goods that require assistance in locating and comparing observable attributes (Shi et al., 2022; Wirtz & Mattila, 2001). In contrast, thin chatbots signal competence, discipline, and analytic precision, fitting credence goods whose quality is difficult to verify and thus require expert-like, cognitively guided decision support (Shi et al., 2020; Basu, 2018). This logic mirrors the distinction between search goods which allow pre-purchase evaluation, and credence goods, such as repairs, diagnosis, or supplements, which remain uncertain even after consumption (Wirtz & Mattila, 2001; Basu, 2018). Online environments further reinforce this divide: search goods benefit from abundant comparison tools, whereas credence goods demand diagnostic guidance (Zhai et al., 2017). Together, these perspectives justify matching heavy–search and thin–credence chatbots to enhance performance expectancy and reduce effort.

2.3 Effect of congruence between chatbot body size and product type on performance expectancy and effort expectancy

Performance expectancy reflects the belief that a technology improves task performance (Søren Eiskjær et al., 2023), while effort expectancy refers to the perceived ease of use (Davis, 1989) and, for chatbots, the difficulty of interaction (Gursoy et al., 2019). When a thin chatbot signaling competence and analytic precision, is paired with credence goods, or a heavy chatbot conveying warmth and supportive guidance, is paired with search goods, consumers perceive stronger congruency between the chatbot's qualities and task demands. This perceived fit signals that the chatbot is well-suited to assist with the decision, thereby increasing performance expectancy and reducing effort expectancy.

H1: Chatbots with a thin body size (vs. heavy) will yield higher performance expectancy and lower effort expectancy when customers buy credence goods.

H2: Chatbots with a heavy body size (vs. thin) will yield higher performance expectancy and lower effort expectancy when customers buy search goods.

2.4 Moderating role of long-term orientation

Long-term orientation reflects a willingness to forgo short-term convenience for future gains, emphasizing perseverance and long-range goals (Hofstede & Bond, 1988). Short-term–oriented consumers prioritize immediate outcomes and show lower adaptability to technological change (Ganguly et al., 2010; Marcus & Krishnamurthi, 2009), making them more resistant to marketing innovations (Hsu et al., 2010). LTO also shapes how users evaluate usefulness and future benefits in digital technologies (Hallikainen & Laukkanen, 2018; Jung et al., 2020). Thus, low-LTO consumers rely more on body-size congruence (thin–credence, heavy–search), whereas high-LTO consumers focus on long-term diagnostic value, reducing sensitivity to such cues. We hpothesize:

H3a. The positive effect of congruency between chatbot body size and product type (thin–credence, heavy–search) on performance expectancy will be stronger among consumers with low LTO than among those with high LTO.

H3b. The negative effect of congruency between chatbot body size and product type (thin–credence, heavy–search) on effort expectancy will be stronger among consumers with low LTO than among those with high LTO.

2.6 Behavioral engagement with chatbots

Behavioral engagement reflects users' active participation with chatbots, shown through utterances and cognitive or motivational responses (He et al., 2024). When chatbot body size matches product-type needs, thin for competence-driven credence goods, heavy for supportive search goods, users perceive higher performance expectancy and lower effort (Gursoy et al., 2019; Zhu et al., 2022). This congruence builds trust and encourages longer, more meaningful engagement.

H4: Performance expectancy is positively related to consumers' behavioral engagement with chatbots.

H5: Effort expectancy is negatively related to consumers' behavioral engagement with chatbots.

Conceptual framework capturing all the proposed hypotheses is shown in Figure 1.

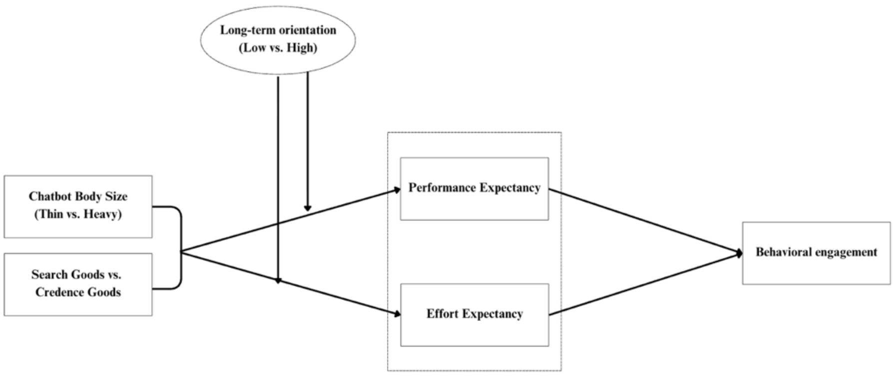

Figure 1. Conceptual framework

2. Methodology

A total of 180 CloudResearch Connect participants were randomly assigned to a 2 (chatbot body size: thin vs. heavy) × 2 (product type: search vs. credence) between-subjects design. Participants read a shopping scenario containing an image and description of either a thin chatbot (BMI < 18.5) or a heavy chatbot (25 ≤ BMI < 30), based on CDC guidelines. In the search-good condition, they imagined browsing the fictitious Sophia Mall to buy a mystery novel and interacting with a chatbot recommending a book and a 15% discount. In the credence-good condition, they imagined visiting SkyGuard.com to purchase travel insurance and viewed a parallel dialogue describing coverage and a 15% promotion. After the scenario, participants completed manipulation checks for chatbot body size (1 = definitely thin; 7 = definitely heavy; Bryksina et al., 2020) and a categorical BMI check. They then responded to validated scales measuring performance expectancy (Meng, Lu, & Xu, 2025), effort expectancy (Gursoy et al., 2019), behavioral engagement (He et al., 2024), and long-term orientation (Bearden, Money, & Nevins, 2006), all on 7-point Likert scales.

3. Major Results

Testing H1-H2. Two two-way ANOVAs revealed significant effects of Body size and Product type on PE and EE. For PE, Body size ($F(1,176) = 39.82$, $p < .001$) and Product type ($F(1,176) = 4.89$, $p = .028$) showed main effects, with a strong interaction ($F(1,176) = 17.22$, $p < .001$): thin chatbots increased PE for credence goods (M = 6.00 vs. 5.42), whereas fat chatbots increased PE for search goods (M = 5.58 vs. 6.38). For EE, Body size ($F(1,176) = 5.14$, $p = .024$), Product type ($F(1,176) = 4.31$, $p = .039$), and their interaction ($F(1,176) = 48.05$, $p < .001$) were significant: thin chatbots reduced EE for credence goods (M = 3.92 vs. 4.88), while fat chatbots reduced EE for search goods (M = 3.63 vs. 5.40). These results strongly support H1 and H2. Interaction Plot: Body Size x Product Type on PE, EE in Figure 2

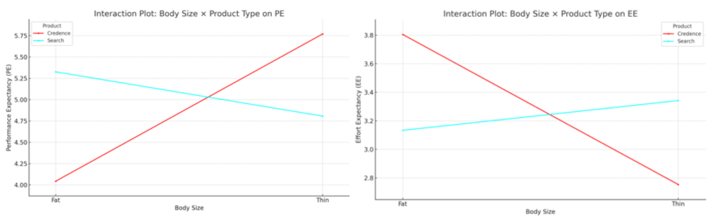

Figure 2. Interaction Plot: Body Size x Product Type on PE, EE in Figure 2

Testing H3a-3b. Three-way ANOVAs showed significant Body size × Product × LTO interactions for both PE ($F(15,152) = 9.48$, $p < .001$) and EE ($F(15,152) = 14.41$, $p < .001$). Low-LTO consumers demonstrated stronger congruency effects, with higher PE in thin–credence (M = 5.38) and heavy–search (M = 4.94), alongside lower PE in mismatched pairs such as thin–search (M = 3.47) and heavy–credence (M = 3.38). A similar pattern emerged for EE, where low-LTO participants reported reduced effort in thin–credence (M = 2.79), but elevated effort in mismatched thin–search (M = 3.73) and heavy–credence (M = 4.22). In contrast, high-LTO consumers exhibited consistently stable evaluations across all conditions (PE ≈ 5.42–6.00; EE ≈ 2.73–3.17). These patterns support H3a and H3b. Interaction Plot: Body Size x Product Type on PE, EE for High versus Low LTO in Figure 3

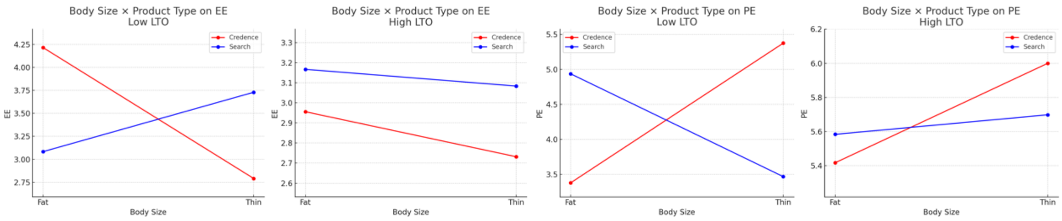

Figure 3. Interaction Plot: Body Size x Product Type on PE, EE for High versus Low LTO

Testing H4-H5. A multiple regression showed that both performance expectancy and effort expectancy significantly predicted behavioral engagement ($R^2 = .762$). Performance expectancy positively predicted engagement ($b = 0.77$, $p < .001$), supporting H4. Effort expectancy negatively predicted engagement ($b = –0.17$, $p < .001$), supporting H5.

4. Implications

As a consumer choice, businesses are optimizing chatbots for improved customer acceptance and shopping experience. We have identified that the relationship between chatbot body size and product type improves engagement and trust and it is moderated depending on the long-term orientation (LTO). For credence goods — like dietary supplements or legal and financial services — thin chatbots perform better because they signal competence, analytic precision and high self-control, cues customers often rely on when it's difficult to verify product quality. Heavy chatbots are also effective in search goods as they convey warmth, friendliness, and helpfulness, making them ideal for helping customers make an information-based decision. Notably, low-LTO consumers are very responsive to these congruent matches, while high-LTO consumers, focused on reliability and future value, have minimal sensitivity to body-based cues. In a nutshell, by aligning the chatbot development to product attributes with users' temporal mindset firms might have a more effective strategy towards improving online customer experience and sales.

References

Balafoutas, L., & Kerschbamer, R. (2020). Credence goods in the literature: What the past fifteen years have taught us about fraud, incentives, and the role of institutions. *Journal of Behavioral and Experimental Finance*, *26*, 100285.

Basu, S. (2018). Information search in the internet markets: Experience versus search goods. Electronic Commerce Research and Applications, 30, 25–37.

Bearden, W. O., Money, R. B., & Nevins, J. L. (2006). A measure of long-term orientation: Development and validation. *Journal of the Academy of Marketing Science*, *34*(3), 456-467.

Bryksina, O., Wang, L., & Mai-McManus, T. (2020). How Body Size Cues Judgments on Person Perception Dimensions. *Social Psychological and Personality Science*, *12*(6), 194855062096367.

Cassiano, G. S., Carvalho-Ferreira, J. P., Buckland, N. J., Ulian, M. D., & da Cunha, D. T. (2022). Are Dietitians With Obesity Perceived as Competent and Warm? Applying the Stereotype Content Model to Weight Stigma in Brazil. *Frontiers in Nutrition*, *9*.

Chen, J., Guo, F., Zhang, Z., Tian, X., & Ham, J. (2025). Effects of Chatbots with Anthropomorphic Visual and Auditory Cues on Users' Affective Preference: Evidence from Event-Related Potentials. *International Journal of Human-Computer Interaction*, 1–16.

Chen, J., Li, M., & Ham, J. (2024). Different dimensions of anthropomorphic design cues: How visual appearance and conversational style influence users' information disclosure tendency towards chatbots. *International Journal of Human-Computer Studies*, *190*, 103320–103320.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

Ganguly, B., Dash, S. B., Cyr, D., & Head, M. (2010). The effects of website design on purchase intention in online shopping: the mediating role of trust and the moderating role of culture. *International Journal of Electronic Business*, *8*(4-5), 302-330.

Grewal, D., Kroschke, M., Mende, M., Roggeveen, A. L., & Scott, M. L. (2020). Frontline Cyborgs at Your Service: How Human Enhancement Technologies Affect Customer Experiences in Retail, Sales, and Service Settings. *Journal of Interactive Marketing*, *51*(1), 9–25.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*(1), 157–169.

Hallikainen, H., & Laukkanen, T. (2018). National culture and consumer trust in e-commerce. *International journal of information management*, *38*(1), 97-106.

He, L., Braggaar, A., Basar, E., Krahmer, E., Antheunis, M., & Wiers, R. (2024, July). Exploring user engagement through an interaction lens: what textual cues can tell us about human-chatbot interactions. In *Proceedings of the 6th ACM Conference on Conversational User Interfaces* (pp. 1-14).

Hill, J., Randolph Ford, W., & Farreras, I. G. (2015). Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in Human Behavior*, *49*(3), 245–250.

Hofstede, G., & Bond, M. H. (1988). The Confucius connection: From cultural roots to economic growth. *Organizational dynamics*, *16*(4), 5-21.

Hsu, Y., Hsu, L., & Yeh, C. W. (2010). A cross-cultural study on consumers' level of acceptance toward marketing innovativeness. *African Journal of Business Management*, *4*(6), 1215.

Huang, P., Lurie, N. H., & Mitra, S. (2009). Searching for Experience on the Web: An Empirical Examination of Consumer Behavior for Search and Experience Goods. *Journal of Marketing*, *73*(2), 55–69.

Jiang, T., Huang, C., Xu, Y., & Zheng, H. (2025). Cognitive vs. emotional empathy: exploring their impact on user outcomes in health-assistant chatbots. *Behaviour & Information Technology*, 1–16.

Jung, T., Tom Dieck, M. C., Lee, H., & Chung, N. (2020). Moderating role of long-term orientation on augmented reality adoption. *International Journal of Human–Computer Interaction*, *36*(3), 239-250.

Keeling, K., McGoldrick, P., & Beatty, S. (2010). Avatars as salespeople: Communication style, trust, and intentions. *Journal of Business Research*, *63*(8), 793–800.

Krille, S., Müller, A., Steinmann, C., Reingruber, B., Weber, P., & Martin, A. (2012). Self- and social perception of physical appearance in chest wall deformity. *Body Image*, *9*(2), 246–252.

Li, M., & Wang, R. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand. *Journal of Retailing and Consumer Services*, *71*, 103209.

Marcus, A., & Krishnamurthi, N. (2009, July). Cross-cultural analysis of social network services in Japan, Korea, and the USA. In *International Conference on Internationalization, design and global development* (pp. 59-68). Berlin, Heidelberg: Springer Berlin Heidelberg.

Mattila, A. S., & Wirtz, J. (2002). The impact of knowledge types on the consumer search process: An investigation in the context of credence services. *International Journal of Service Industry Management*, *13*(3), 214-230.

Meng, H., Lu, X., & Xu, J. (2025). The impact of chatbot response strategies and emojis usage on customers' purchase intention: the mediating roles of psychological distance and performance expectancy. *Behavioral Sciences*, *15*(2), 117.

Schillaci, C. E., de Cosmo, L. M., Piper, L., Nicotra, M., & Guido, G. (2024). Anthropomorphic chatbots' for future healthcare services: Effects of personality, gender, and roles on source credibility, user satisfaction, and intention to use. *Technological Forecasting and Social Change*, *199*, 123025.

Shi, B., Mai, Y., & Mo, M. (2022). Chubby or thin? Investigation of (in)congruity between product body shapes and internal warmth/competence. *Journal of Experimental Psychology: Applied*.

Shi, S., Gong, Y., & Gursoy, D. (2020). Antecedents of Trust and Adoption Intention toward Artificially Intelligent Recommendation Systems in Travel Planning: a Heuristic–Systematic Model. *Journal of Travel Research*, *60*(8), 004728752096639.

Søren Eiskjær, Casper Friis Pedersen, Skov, S., & Andersen, M. (2023). Usability and performance expectancy govern spine surgeons' use of a clinical decision support system for shared decision-making on the choice of treatment of common lumbar degenerative disorders. *Frontiers in Digital Health*, *5*.

Wang, Y.-C., Chi, O. H., Saito, H., & Lu, Y. (Darcy). (2024). Conversational AI chatbots as counselors for hospitality employees. *International Journal of Hospitality Management*, *122*, 103861.

Yao, R., Qi, G., Wu, Z., Sun, H., & Sheng, D. (2024). Digital human calls you dear: How do customers respond to virtual streamers' social-oriented language in e-commerce livestreaming? A stereotyping perspective. *Journal of Retailing and Consumer Services*, *79*, 103872–103872.

Zhai, X., Ding, Y., & Wang, F. (2017). The interactions between e-shopping and store shopping in the shopping process for search goods and experience goods. *Information Technology & People, 30*(1), 174–196.

Zhu, Y., Zhang, J., Wu, J., & Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. *Journal of Business Research*, *150*, 642–652.