Human-Robot Interaction in E-Commerce: The Role of Personality Traits and Chatbot Mechanisms – A Neuromarketing Research

Yu-Wen Chang
Department of Management Information Systems
National Chengchi University
Taipei, Taiwan
irenechangcv6@gmail.com

Shih-Yi Chien
Department of Management Information Systems
National Chengchi University
Taipei, Taiwan
sychien@nccu.edu.tw

Yao-Cheng Chan
School of Information
University of Texas at Austin
Austin, Texas, USA
ycchan@utexas.edu

Ching-Chih Tsao
Cornell Tech
New York, New York, USA
ct649@cornell.edu

ABSTRACT

This paper explores the intersection of neuromarketing, e-commerce, and human-robot interaction by investigating the impact of personality traits on user satisfaction, purchase intention, and brainwave patterns across different chatbot models (rule-Based vs generative AI) and platforms (virtual chatbots vs humanoid robots). The study introduces Generative AI chatbots to e-commerce websites, comparing their effectiveness with rule-based chatbots. Additionally, physical robots are included as a reference group to assess the effects of virtual and physical robots in shopping assistance. The manipulation of three personality traits (introvert, ambivert, and extrovert) in both online and offline settings enriches the understanding of user behavior in diverse scenarios. Data collection involves EEG measurements, system logs, and surveys to capture subjective perceptions, unconscious reactions, and decision-making processes. Ultimately, the research seeks to provide valuable insights for the development of human-computer interaction design, contributing to the formulation of design guidelines adapted specifically for the e-commerce landscape.

CCS CONCEPTS

• Human-centered computing • Human computer interaction (HCI) • HCI design and evaluation methods • Laboratory experiments

HRI'24 Companion, March 11–14, 2024, Boulder, CO, USA.

ACM ISBN 979-8-4007-0323-2/24/03…$15.00.
DOI: https://doi.org/10.1145/3610978.3640742

KEYWORDS

Neuromarketing, human-robot interaction, Generative AI, personality traits, electroencephalogram (EEG)

ACM Reference format:

Yu-Wen Chang, Shih-Yi Chien, Yao-Cheng Chan and Ching-Chih Tsao. 2024. Human-Robot Interaction in E-Commerce: The Role of Personality Traits and Chatbot Mechanisms – A Neuromarketing Research. In Proceedings of 2024 ACM Conference on Human-Robot Interaction (HRI'24 Companion), March 11-14, 2024, Boulder, CO, USA. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3610978.3640742

1 INTRODUCTION AND LITERATURE REVIEW

Within the academic domain, neuromarketing has gathered significant popularity and attention, combining elements of marketing, neuroscience, economics, decision theory, and psychology [1]. The purpose of neuromarketing is to gain insights into customer behavior, enabling effective prediction of customer preferences in the decision-making process [2]. Previous studies have mainly focused on experiments based on the design and stimuli of web pages on e-commerce platforms [3, 4]. However, in recent years, chatbots on e-commerce websites have played a crucial role in addressing user shopping concerns. Research has affirmed that chatbots can influence consumer purchasing decisions and significantly enhance user experience [5]. The development of generative artificial intelligence (Generative AI) has further driven the application of chatbots. Generative AI, utilizing machine learning technology, can understand user input and provide more personalized responses. However, past research has primarily focused on rule-based chatbot studies [6] with limited exploration of the application of generative AI chatbots on e-commerce websites and a lack of comparative research between these two types of chatbots. Therefore, this experiment will introduce generative AI chatbots to explore their application on e-commerce websites and compare their effectiveness with rule-based chatbots. The goal is to bridge the research gap and understand whether generative AI chatbots can offer a more personalized chat experience or potentially limit user satisfaction. We will adopt the classification proposed by [7], positioning online chatbots as "telepresent robots," where users interact with a robot with a physical presence in the real world. Still, the interaction is facilitated through a computer monitor, television, or projector screen.

In addition to the telepresent robot experiment, the study introduces physical robots as a reference group, referred to as "copresent robots," in which individuals interact face-to-face with the robot. Existing research suggests that non-verbal features of robots play a crucial role in human-robot interaction, capturing user attention and enhancing overall engagement [8]. Existing studies have covered the interaction between Chatbots and humanoid robots [9]. However, to the best of my knowledge, there is a lack of research that specifically compares the preferences for different robot types between the two. Consequently, this experiment aims to systematically compare the impact of virtual (telepresent) and physical (copresent) robots on users' purchasing decisions and preferences in the realm of shopping assistance.

Furthermore, previous studies on chatbot for customer care usually focuses on the generation of grammatically correct responses, overlooking various factors that could potentially impact user experience [10]. To gain a deeper understanding of how different personality traits influence interaction, this experiment will manipulate three distinct personality traits (introvert, ambivert, and extrovert) for both virtual (telepresent) and physical (copresent) robots. This will help us understand how personality traits affect users' interaction experiences with different robots, enriching our understanding of user behavior in different scenarios. Regarding data collection, this study will use surveys to understand participants' subjective perceptions and preferences. However, surveys have limitations in capturing or explaining real-time consumer decision-making processes. Participants may not accurately express their thoughts or emotions due to personal biases. Therefore, this study incorporates EEG measurements to detect continuous changes in brain activity to evaluate participants' unconscious reactions and sensory responses. EEG functionality aims to objectively analyze changes in participants' brainwaves during interactions with different robots, exploring emotional changes and preference choices. This aims to align with and complement subjective survey results, addressing the existing research gap between brainwave patterns and specific cognitive processes or personality traits. Additionally, system logs will be collected to understand the time and decision-making spent by participants when interacting with different robots on the e-commerce website.

The following are the research questions and hypotheses:

RQ1. Will different personality traits impact interpersonal impressions?
H1a: User Satisfaction will notably differ based on users' perceptions of the personality traits of a chatbot.
H1b: Users' Purchase Intention will vary notably based on their perceived personality traits of a chatbot.
H1c: Brainwave patterns will exhibit notable differences among users with different personality trait preferences when interacting with a chatbot.

RQ2. Will different chatbot mechanisms impact interpersonal impressions?
H2a: User Satisfaction will notably differ between interactions with a Rule-Based chatbot and a GAI-based chatbot.
H2b: Purchase Intention will vary notably based on whether users interact with a Rule-Based or a GAI-Based chatbot.
H2c: Brainwave patterns will exhibit notable differences among users interacting with a Rule-Based chatbot compared to a GAI-based chatbot.

RQ3. Will social presence impact interpersonal impressions?
H3a: User Satisfaction will notably differ between interactions with a chatbot and a humanoid robot.
H3b: Users' Purchase Intention will vary notably based on whether they interact with a chatbot or a humanoid robot.
H3c: Brainwave patterns will exhibit notable differences among users interacting with a chatbot compared to those interacting with a humanoid robot.

In summary, this research attempts to answer key research questions and validate hypotheses related to the impact of personality traits and different types of robots on user satisfaction, purchase intention, and brainwave patterns. The findings are expected to provide practical insights for future human-computer interaction design and contribute to the evolving field of neuromarketing.

2 METHODOLOGY

2.1 Apparatus

The test session environments will include a website (online session) and a robot agent (offline session). A website will be developed to simulate an e-commerce environment and create an online shopping experience. The participants will be asked to collaborate with the chatbot on the website to purchase a planned product. During the shopping process, the participants will receive product recommendations from a chatbot based on the participants' input query. The chatbot will utilize two distinct mechanisms: a Rule-Based model and a Generative AI model. This manipulation aims to investigate the impact of different chatbot types on participants' decision-making processes and their acceptance of the technology. On the offline side, a physical humanoid robot, Pepper, will be introduced to facilitate a different kind of interaction for comparison. In addition, an electroencephalogram (EEG) headset will be used to measure participants' cognitive activity.

2.2. Virtual Chatbot and Humanoid robot Personality

This experiment will involve two types of chatbots: online (virtual) chatbots and offline (physical) robots. The online (virtual) chatbot will be further divided into Rule-based chatbots and GAI chatbots. The primary distinction between the two will lie in their communication methods. The Rule-based chatbot will rely on predetermined rules and questions, offering users predefined options that lead to desired answers. On the other hand, the GAI chatbot will utilize machine learning models, employing natural language processing (NLP) to understand the real meaning of user input and provide personalized responses. We will use the ChatGPT API to implement the AI chatbot. OpenAI has made the ChatGPT API available to developers and the public, allowing users to call ChatGPT in their interface and directly display the results using the API key. Our practical approach will involve utilizing OpenAI's latest "gpt-3.5-turbo" model, trained up to September 2021. This model will enable users to personalize the role of the AI chatbot, adjusting its personality traits by customizing the language and tone. Additionally, by training the model with specific data, the GAI chatbot can enhance its understanding of particular products, services, and customer queries, ensuring accurate and helpful user responses. As for the user interface, we will employ Gradio, an open-source Python library for building machine-learning solutions, to create a simple web interface accessible both locally and on the web.

For the offline (physical) robot, we will select the Pepper robot. The Pepper robot possesses the capability of arm and finger movement, allowing it to execute various gestures. Additionally, Pepper features speech recognition and synthesis technology, enabling it to comprehend and respond to human vocal commands. Overall, Pepper has the capability to perform various tasks, including answering questions, providing information, playing media content, and executing specific actions. This will enhance the emotional connection with users, making it an ideal choice for the experiment. Furthermore, in human-machine interaction, the personality traits of robots play a crucial role by directly influencing the user's emotional engagement and satisfaction. Different personality traits may lead to varied expectations and responses to humans. To infuse personality traits into the chatbots, the experiment will introduce nonverbal cues (including textual and gestural elements), generating three personality types (introverted, ambivert, and extroverted). Textual manipulations will involve adjusting word count, information structure, and visual effects [11, 12]. In terms of gestural design, the offline (physical) Pepper robot will operate by altering movement frequency, speed, and size [13, 14], while the online (virtual) chatbot will present robot actions through video.

2.3. EEG Headset

In this study, we will utilize the EMOTIV EPOC X, a wireless EEG headwear device equipped with 14 channels, to collect participants' brainwave patterns. This will be employed to investigate the accuracy with which the power of EEG signals can differentiate between various consumer preferences and predict decision-making incidents.

The EEG device employs fourteen electrodes to measure participants' cognitive states and decision-making processes. Among these electrodes, eight (AF3, F7, AF4, F8, F3, FC5, FC6, and F4) are placed on the frontal cortex to capture brain activity associated with cognition. Two electrodes (T7 and T8) on the temporal lobe handle short-term memory, balance, and emotions. Another two electrodes (P7 and P8) on the parietal lobe primarily contribute to sensory perception and integration. Two electrodes (O1 and O2) on the occipital lobe handle visual processing, image recognition, and perception.

In this study, our main focus will be on the alpha and beta brainwaves recorded from the eight electrodes placed on the frontal cortex. This emphasis is due to our research centering on consumer preferences and decision-making processes. Previous studies have indicated that alpha waves can predict product preferences, while beta waves are particularly useful for measuring appropriate emotional and cognitive processes [15]. Beta waves can be further categorized into three frequency bands using the Fourier Transform, each associated with distinct cognitive activities Low beta (12.5~16 Hz) is associated with Quiet, focused, and introverted concentration activities, and Mid-range beta (16.5~20 Hz) is correlated with increased energy, anxiety, and performance. High beta (20.5~28 Hz) relates to stress, anxiety, paranoia, and heightened arousal.

Additionally, research has confirmed that EEG brainwaves, especially in the centro-parietal and frontal regions (Cp3, Cpz, and Fp1), can be used to predict decision-making [16]. Simultaneously, the left and right brain hemispheres play opposite roles in perceiving and expressing emotions: the left hemisphere dominates positive emotions, while the right hemisphere dominates negative emotions. Studies suggest that an increase in theta and alpha waves in the left frontal region signifies a preference for "liking," whereas in the right frontal region, it indicates a preference for "disliking" [16]. The accuracy of decision differentiation between "liking" and "disliking" is highest at the F4 electrode [16]. Hence, in order to identify participants' cognitive states and brain activities, our study will measure the alpha (α) and beta (β) brainwaves in the frontal cortex significantly associated with human preferences, consciousness, and cognitive processes.

2.4. Cognitive Measurements

In addition to the EEG measures that will evaluate cognitive effects in various conditions, multiple questionnaires will be employed to capture participants' attitudes and perceptions toward the tasks and robotic agents during the experiment.

Negative attitudes toward robots will be assessed using the Negative Attitudes Toward Robots Scale (NARS) [17], which includes three dimensions: negative attitudes toward situations of interaction with robots, negative attitudes toward the social influence of robots, and negative attitudes toward emotions in interaction with robots. Participants will rate statements such as "I feel that if I depend on robots too much, something bad might happen." The Robotic Social Attributes Scale (RoSAS) [18] will be employed to identify participants' judgments of the social attributes of robots, focusing on dimensions like warmth, competence, and discomfort. Participants will provide ratings based on the association of words with the category "robots." The NASA-TLX survey [19] will be utilized to assess participants' perceived workload during experimental tasks, considering constructs such as mental demand, physical demand, temporal demand, performance, effort, and frustration. Participants will express their experiences regarding factors like "How hard did you have to work to accomplish your level of performance?" Items from the BFI-44 [20] related to "Extroversion" will be adopted to evaluate the perceived personality trait of extroversion in robots. Participants will use a 5-point differential scale to express perceptions of the robot's extroversion, considering statements like "I think the robot is talkative" and "The robot is energetic." A set of three survey items will be utilized to assess participants' tendency toward making purchases from the robots [21, 22]. Participants will express their perspectives on aspects like "How likely are you to consider purchasing from this robot?" using a 5-point scale.

Additionally, at the end of the experiment a Serving Rating will be included, prompting participants to rank their preference among the three different robots. This control variable aims to understand participants' preferences and how they rank the robots based on their personalities and interactions. These carefully selected measures will comprehensively understand participants' attitudes, perceptions, and preferences in response to various experimental conditions and robotic agents.

2.5. Participants and Procedures

The experiments will be divided into two sessions. Every participant will go through these two sessions once. In the first session, participants will be instructed to shop on the e-commerce platform and collaborate with the chatbot in the bottom right corner of the screen. Their objective will be to choose the most appropriate birthday gift based on a provided scenario. Different chatbot mechanisms and personality traits will be randomly presented to the participants (figure 1). The chatbot will assume the role of a system recommender, offering product recommendations based on participants' stated product preferences. This setup aims to assist participants in efficiently completing the purchase process on the e-commerce platform. After brief intermissions, the second session will involve participants interacting with a humanoid robot while maintaining consistent experimental conditions.

After every session, subjective questionnaires will be employed to gain insights into participants' perceptions of the research content. Objective measurements including system logs and brainwave data will be collected during the two sessions. System logs will document users' interactions on the e-commerce website, including decision-making time, to assess the efficiency and preferences between the two interaction methods. Simultaneously, the use of a brainwave sensor will record the brainwave regions and waveform significance of the participant, corresponding to decision-making and preferences throughout the experiment. These data will then be analyzed through statistical analysis and machine learning techniques to potentially uncover more intricate patterns and correlations. This dual-method approach aims to thoroughly understand both subjective and objective aspects of user engagement with the chatbot across different personality traits and platforms.

The act of purchasing the intended product will serve as a means to assess participants' buying behavior and associated brainwaves between the two chatbot types. Furthermore, including different personality traits will allow an exploration of how diverse personalities influence chatbot interactions, subsequently impacting purchasing decision-making. The introduction of a humanoid robot will further facilitate the analysis of participants' perceptions regarding the disparities between virtual and physical robot interactions.

	Introvert	**Ambivert**	**Extrovert**
Rule-Based chatbot	Textual + Gestural + Introvert	Textual + Gestural + Ambivert	Textual + Gestural + Extrovert
GAI chatbot	Textual + Gestural + Introvert	Textual + Gestural + Ambivert	Textual + Gestural + Extrovert

Figure. 1: Experimental conditions.

3. EXPECTED CONTRIBUTION

This study aims to evaluate the efficiency of user interactions with chatbots compared to humanoid robots in an e-commerce scenario. The results may reveal which medium (virtual chatbot or physical humanoid robot) more effectively assists users in decision-making and completing the purchase process. Simultaneously, by incorporating different personality traits, the research seeks to explore how personality differences influence user interactions with both chatbots and humanoid robots. The results may indicate whether certain personality types prefer a particular interaction mode and how personality impacts the decision-making process. In summary, this study anticipates providing a comprehensive understanding of user engagement across various personality traits and platforms, offering valuable insights for designing and enhancing virtual assistants in the e-commerce setting.

REFERENCES

[1] Morin, C. (2011). Neuromarketing: the new science of consumer behavior. Society, 48(2), 131-135.

[2] Yoon, C., Gutchess, A. H., Feinberg, F., & Polk, T. A. (2006). A functional magnetic resonance imaging study of neural dissociations between brand and person judgments. Journal of consumer research, 33(1), 31-40.

[3] Hsu, L., & Chen, Y. J. (2020). Neuromarketing, subliminal advertising, and hotel selection: An EEG study. Australasian Marketing Journal, 28(4), 200-208.

[4] Babaç, E., & Yüncü, H. R. (2022). Determination of user experience on food business websites by using Neuromarketing techniques. Tourism & Management Studies, 18(3), 49-64.

[5] Lo Presti, L., Maggiore, G., & Marino, V. (2021). The role of the chatbot on customer purchase intention: towards digital relational sales. Italian Journal of Marketing, 2021(3), 165-188.

[6] Abd-Alrazaq, A. A., Alajlani, M., Alalwan, A. A., Bewick, B. M., Gardner, P., & Househ, M. (2019). An overview of the features of chatbots in mental health: A scoping review. International Journal of Medical Informatics, 132, 103978.

[7] Li, J. (2015). The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents. International Journal of Human-Computer Studies, 77, 23-37.

[8] Johanson, D. L., Ahn, H. S., MacDonald, B. A., Ahn, B. K., Lim, J., Hwang, E., … & Broadbent, E. (2019). The effect of robot attentional behaviors on user perceptions and behaviors in a simulated health care interaction: randomized controlled trial. Journal of medical Internet research, 21(10), e13667.

[9] Kuo, P. H., Lin, S. T., Hu, J., & Huang, C. J. (2021). Multi-sensor context-aware based chatbot model: An application of humanoid companion robot. Sensors, 21(15), 5132.

[10] Hu, T., Xu, A., Liu, Z., You, Q., Guo, Y., Sinha, V., … & Akkiraju, R. (2018, April). Touch your heart: A tone-aware chatbot for customer care on social media. In Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-12).

[11] Lippa, R. A., & Dietz, J. K. (2000). The relation of gender, personality, and intelligence to judges' accuracy in judging strangers' personality from brief video segments. Journal of Nonverbal Behavior, 24(1), 25–43.

[12] Okita, S. Y., Ng-Thow-Hing, V., & Sarvadevabhatla, R. (2009). Learning together: ASIMO developing an interactive learning partnership with children. Proceedings - IEEE International Workshop on Robot and Human Interactive Communication, 1125–1130.

[13] Kim, H., Kwak, S. S., & Kim, M. (2008). Personality design of sociable robots by control of gesture design factors. In Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN. https://doi.org/10.1109/ROMAN.2008.4600715

[14] Otterdijk, M. Van, Song, H., Tsiakas, K., Van Zeijl, I., & Barakova, E. (2022). Nonverbal Cues Expressing Robot Personality-A Movement Analysts Perspective. RO-MAN 2022 - 31st IEEE International Conference on Robot and Human Interactive Communication: Social, Asocial, and Antisocial Robots,1181–1186.https://doi.org/10.1109/RO- MAN53752.2022.9900647

[15] Wu, Y. L., & Chen, P. C. (2022). Neurophysiology of sensory imagery: An effort to improve online advertising effectiveness through science laboratory experimentation. Information & Management, 103708.

[16] Golnar-Nik, P., Farashi, S., & Safari, M. S. (2019). The application of EEG power for the prediction and interpretation of consumer decision-making: A neuromarketing study. Physiology & behavior, 207, 90-98.

[17] Nomura, T., Suzuki, T., Kanda, T., & Kato, K. (2006). Measurement of negative attitudes toward robots. Interaction Studies. Social Behaviour and Communication in Biological and Artificial Systems, 7(3), 437-454.

[18] Carpinella, C. M., Wyman, A. B., Perez, M. A., & Stroessner, S. J. (2017, March). The robotic social attributes scale (RoSAS) development and validation. In Proceedings of the 2017 ACM/IEEE International Conference on human-robot interaction (pp. 254-262).

[19] Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In Advances in psychology (Vol. 52, pp. 139-183). North-Holland.

[20] John, O.P., The big five inventory—versions 4a and 54. (No Title), 1991.

[21] Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1. Journal of applied social psychology, 32(4), 665-683.

[22] Shin, Y. H., Im, J., Jung, S. E., & Severt, K. (2018). The theory of planned behavior and the norm activation model approach to consumer behavior regarding organic menus. International Journal of Hospitality Management, 69, 21-29.