Journal of Business Research 145 (2022) 892–904

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Let me transfer you to our AI-based manager: Impact of manager-level job titles assigned to AI-based agents on marketing outcomes

Yongwoog "Andy" Jeon

Northern Illinois University, Department of Marketing, College of Business, Barsema Hall, 740 Garden Road, DeKalb, IL 60115, United States

A R T I C L E I N F O

Keywords:
Artificial intelligence (AI)
Natural Language Processing (NLP)
Chatbot
Customer representative
Customer manager
Heuristic judgment
AI-driven marketing outcomes

A B S T R A C T

This paper examines to what extent the job titles assigned to AI agents can influence the customer's perception of these agents and ultimately their marketing outcomes such as customer satisfaction, brand attitude, and intention to buy AI-recommended products. Also, this study explores how customers perceive the AI agent as the manager working with either a human or an AI representative. Across three experiments (using a scenario or a combination of a scenario and the real AI chatbot), the study shows that consumers perceive the AI manager more positively in terms of likeability, knowledgeability, and trustworthiness than the AI representative and the human manager. The customers perceive the AI manager more positively when they are transferred to the AI manager from a representative of the same kind (AI) than from a human representative. Further, the job titles given to the AI agents are found to have favorable downstream effects on customer satisfaction, brand attitude, and the customers' intentions to buy the products recommended during the chat by the AI manager.

1. Introduction

Artificial intelligence (AI)-powered conversational agents, or simply chatbots, have been increasingly used in business, especially in the area of online customer services (Pantano & Pizzi, 2020). The use of chatbots in business increased by 92% from 2019 to 2020 (Kilens, 2020). Also, around a quarter of the global population was estimated to use chatbots in 2019, and five billion dollars are expected to be invested in chatbots by 2021 (OPUS, 2018). One of the benefits of the AI applications such as chatbot for the company or organization is the cost (Davenport, Guha, Grewal, & Bressgott, 2020). Chatbots can help reduce customer service costs by more than 30% (IBM, 2017). Moreover, fast answers and twenty-four-hour availability are the benefits enjoyed by the chatbot customer service particularly in the times of the pandemic when customers avoid physical contacts with the service employees (Pantano & Pizzi, 2020; Vlačić, Corbo, e Silva, & Dabić, 2021). On online shopping websites, the AI chatbot answers the customer's inquiries about the products, including refunds, product availability, shipping, discounts, and post-purchase complaints. It is also used as a "salesperson" recommending products to customers based on the analysis of the customer's purchase patterns (Adam, Wessel, & Benlian, 2020).

Despite the benefits and increasing usage of the chatbot, customers still seem to have unfavorable perceptions of the AI agents (Userlike, 2020). While customers are somehow willing to interact with an AI-agent first on a chat platform, they still prefer being eventually transferred to and chatting with a human agent (Press, 2019; Userlike, 2020). Customers who do not like chatbots believe that the chatbots provide canned answers only to simple questions, do not know how to solve customer issues, and lack social skills (Elliot, 2018). Overall, customers perceive AI agents to be less likable than human agents. More importantly, a large volume of research has documented that these negative perceptions can inadvertently decrease customer satisfaction even when the agents technically perform well (Dagger, Danaher, Sweeney, & McColl-Kennedy, 2013; Jayanti & Whipple, 2008; Shellenbarger, 2014; Yoo, Arnold, & Frankwick, 2012). In short, the unfavorable perception of AI agents is an issue that needs an effective marketing solution.

In response to this issue of the unfavorable perception toward the AI agents, the authors of this paper proposed and tested a simple tactic: a job title. A job title is a salient perceptual cue from which customers judge what the employee is thought to be capable of by the companies (Grant, Berg, & Cable, 2014; Woolway & Harwood, 2015). Customers form an impression of who an agent is based on the job title, which implicitly conveys information about what the agent is like, such as likeability (i.e., how nice or socially skilled the agent is to the customers), trustworthiness, and knowledgeability to get the job done (Ahearne, Mathieu, & Rapp, 2005). Particularly, given the technical capacities of AI agents, presenting chatbots with the same job titles as those assigned to human agents may change the customers' perceptions

E-mail address: andyjeon@niu.edu.

https://doi.org/10.1016/j.jbusres.2022.03.028
Received 11 July 2021; Received in revised form 10 March 2022; Accepted 14 March 2022
Available online 29 March 2022
0148-2963/

of the AI agents. Despite such a potentially positive impact of the tactic, still, no direct evidence is available to support this prediction.

In this regard, there is another research gap that the current study attempts to fill in. While recent academics and industries started examining the feasibilities of AI-based manager[1] or “AI manager” (Chamorro-Premuzic & Ahmetoglu, 2016; Wesche & Sonderegger, 2019) from the managerial or “the employer” perspective (Granulo, Fuchs, & Puntoni, 2021), little is known about how *customers* would see the AI agents with such a supervisor-level job title. The current paper considers the common practice that the customers chat with multiple customer service agents. That is, in the context of online customer service, when customers or agents think that the issues at hand cannot be solved by the customer representative, these customers are transferred to someone in a higher position, such as the manager. If the customer first sees the human representative followed by the AI manager (so they know that the AI is the boss of the human), how does this expose the unusual hierarchical relation between humans and AI in jobs as well as influence how the customer perceives the agents? If this relation is reversed (AI representative and human manager) or the AI is paired with another AI, how would this influence the customer’s perceptions of the agents? All in all, to what extent does the job title given to an AI agent increase the efficacy of the AI-driven marketing outcomes? By answering these questions, this study attempts to contribute to the literature on the uses of AI technologies, especially chatbots, in business.

All in all, the core objective of the current paper is to empirically examine the marketing impacts of the human job titles including “AI manager” given to the AI agents as a self-presentation tactic. For this purpose, this paper will first discuss theoretical underpinnings that support the feasibility of the proposed tactic, which will be followed by the methodological discussions including the real AI-based chatbot developed and trained for the current research. In turn, the paper will present the empirical findings and their theoretical and practical implications.

2. Theoretical background and hypotheses development

2.1. Perceived likeability and marketing outcomes

Despite the rapidly increasing use of AI agents in customer service, customers still prefer to talk to human agents because they perceive AI agents to be less likeable (Userlike, 2020). These customers like human agents better than AI agents because they believe that the latter are only machines that are not yet advanced enough to answer sophisticated questions or lack social or communicative skills in handling customer demands (Press, 2019). Consequently, the AI agent being perceived as less likeable can have a detrimental impact on returns on investment for AI implementations in customer service, especially given the importance of the concept of “likeability” in customer satisfaction, defined as the extent to which a person is known or perceived to be potentially pleasant (Lamkin, Maples-Keller, & Miller, 2018; Tenney, Turkheimer, & Oltmanns, 2009). Given the perceptually subjective nature of interpersonal contact between customers and frontline employees (Pulles & Hartman, 2017), the *perception* of being likeable can influence the consumers’ satisfaction with the customer service experiences. Specifically, likeable employees tend to result in better consumer satisfaction even more than employees who have similar capabilities but are not likeable (Jayanti & Whipple, 2008). While an abundance of evidence shows that employee likeability is positively linked to customer satisfaction, it lacks a theoretical explanation for the following question: why does a likeable person return a higher degree of customer satisfaction than a less likeable one?

In response, the effect of the employee’s likeability on customer satisfaction can be explained by the Heuristic Judgment Model (Kahneman, 2011). According to this cognitive bias model, a person automatically forms a perception of a person based on the heuristics cues or “mental shortcuts” to quickly judge who the person is (Chaiken & Maheswaran, 1994; Kahneman, 2011). Individuals may delay forming or modify initial impressions of others by carefully seeking, attending to, or scrutinizing other less salient but more substantial pieces of information or “systematic cues” (e.g., actual conversation quality) that are central to the assessment of the person *only when* they are motivated to do so. In the context of the customer service, when judging one’s level of satisfaction with a service employee, customers may use the likeability of the employee as a heuristic based on which they evaluate the satisfactions with the interaction with the customer service employees (Dagger et al., 2013). That is, the first pieces of information about an employee even before actual interpersonal contact (e.g., conversation) tend to be remembered better and be more influential in the customer survey, which relies on retrospective ratings (Fiske & Taylor, 1991).

The Heuristic Judgment Model (Kahneman, 2011) that applies to the perception toward humans can apply to the perceptions toward robots or AI agents. As with human employees, increased likeability is predicted to influence customer satisfaction with the *AI* agents in the customer service context (Adam, Wessel, & Benlian, 2020). This is based on the fundamental adaptive tendency that humans inadvertently attribute human traits such as likeability (e.g., being nice, kind) to non-human entities such as robots (Nass, Steuer, & Tauber, 1994). In this regard, the “computer as social actor” (CASA) paradigm posits that human minds perceive the computer or other machine as a social actor (Nass & Lee, 2001). For example, humans think of, talk with, and behave with the AI chatbot as they do with other humans despite knowing that the AI agent is not human (Nass et al., 1994).

Thus, the employee, whether human or a robot, being likeable is indispensable for customer satisfaction. Indirect evidence for this prediction can be found in the field of human–robot interaction (HCI). HCI scholars have found that “likeability” is one of the key attributes to improve because higher likeability of a robot can lead to a human’s increased willingness to interact with the robot (Salem & Alanadoly, 2020; Sandoval, Brandstatter, Yalcin, & Bartneck, 2020).

2.2. The job title and its effect on the customer’s perception of the employee

If the likeability of the AI agent from the first impression is important for customer satisfaction, then how would consumers judge how likeable the agent is even before the conversation takes place? This question can also be answered by the Heuristic Judgment Model: humans tend to rely on the immediately available pieces of information as a heuristic cue from their environments to judge how likeable a stranger is (Kahneman, 2011). Physical appearance is one example of a heuristic cue. In the context of customer service, a large volume of research has evidenced that physical attractiveness is a heuristic cue that is strongly linked to the perceived likeability of customer service employees, which, in turn, influences customer satisfaction. In contrast, consumers may use systematic cues such as actual conversation quality only in cases when they are explicitly asked to or motivated to evaluate the service based on their observation of such a dimension (Chaiken, 1980; Jayanti & Whipple, 2008). On a text-based online customer chat platform, individuals may judge how likable a customer service agent is based on a limited number of heuristic cues. During the online chat, for example, customers may see the agent’s profile picture from which a customer may get information about the agent’s physical attractiveness while the agent’s voice, facial expression, hand gestures, or other verbal or non-verbal cues are not available (Walther, Loh, & Granka, 2005).

While past research has shown that physical appearance (judged from a profile picture of an online chat platform) as a heuristic cue can

[1] To minimize the confusion that “AI manager” is understood as a manager in charge of dealing with AI technologies, we first stated “AI-based manager” (which refers to “AI customer service manager” in this paper) followed by “AI manager”.

enhance the likeability of AI or human service employees (Lv, Liu, Luo, Liu, & Li, 2021), little attention has been paid to another potentially powerful cue that can increase positive perceptions toward the chatbot: the *job title*. The job title can be seen as a “prominent identity badge” as it forms a strong first impression to the customers (Grant et al., 2014). Scholars (Grant et al., 2014; Kristof-Brown, Zimmerman, & Johnson, 2005) suggest that job titles convey explicit and implicit meanings. Explicitly, a job title can show the hierarchical position or role of the employee within the organization (Baron & Bielby, 1986; Martinez, Laird, Martin, & Ferris, 2008). Implicitly, it can connote the company’s approval that the job title possessor has the key attributes that “fit the job,” which include the authority to handle situations, sufficient abilities, resources to get the job done, trust, knowledge (expertise), and social skills to please customers (i.e., likeability) (Ahearne et al., 2005; Grant et al., 2014; Grewal, Guha, Satornino, & Schweiger, 2021; Neary, 2014; Trautt & Bloom, 1982; Woolway & Harwood, 2015).

Evidence of the impact of title cues on customers’ perceptions of service agents has mostly been accumulated in health-care services (Woolway & Harwood, 2015). Research has generally found that leveling up the professional title of an employee to a higher position results in more positive perceptions of the same employee given the implicit meanings that higher job titles might have (Belbin, 2012; Woolway & Harwood, 2015). While past research has evidenced the positive effects of job titles on customers’ perceptions of employees, little is still known on the extent of the positive effect of the job title when the service agent is non-human: a robot. The lack of knowledge about the impact of assigning a proper job title to a robot may be due to the fact that AI agents typically do not have such titles in practice. While in the customer service area, the typical job titles that customer get to see include the customer representative (or associate). However, the AI agents are rarely given such a title. Amazon, for example, assigns non-specific, ambiguous titles, such as “customer AI (or virtual) chatbot/agent” (Amazon, 2021). This study will compare the efficacy of such conventional wisdom with a new tactic (i.e., assigning a human job title to an AI agent) in boosting positive perceptions toward AI agents according to the Heuristic Judgment Model as discussed (Kahneman, 2011):

H1. The likeability of the customer service agents with a job title (e.g., “customer representative,” “customer manager”) will be higher than the agents with no title.

Further, in the following section, this study also will discuss the extent to which the AI agent will be received more favorably by customers by assigning them with even higher positions than “representative,” such as “manager.”.

2.2.1. AI manager (collaboration between humans and machines)

The manager is broadly defined in the customer service industry as a senior employee or “boss” who “manages” other employees since they are given the position by the company expecting them to be more socially skilled, more knowledgeable, and more trusted (Ansoff, Kipley, Lewis, Helm-Stevens, & Ansoff, 2018). According to the cognitive models of robot perception, in people’s minds, the robot’s role has been regarded stereotypically to be limited to a servant to humans or, at the maximum, a collaborator because having a machine (non-living thing) as a leader is regarded as atypical or counterintuitive (Chamorro-Premuzic & Ahmetoglu, 2016).

However, with rapidly “accelerating” advancements in technologies such as NLP, machine learning, and deep learning (Kurzweil, 2005), AI customer service agents are developed to possess superior expertise (superior information-processing and machine-learning technologies), trustworthiness (because of security technology advancement), and even likeability (NLP and deep learning, which enable natural conversation and social behaviors such as understanding the customer’s emotions) (Höddinghaus, Sondern, & Hertel, 2021; Huang & Rust, 2021; Xiao & Kumar, 2019). For these reasons, recently, industry and academia have started examining the feasibility and efficacy of the robot or AI manager (Chamorro-Premuzic & Ahmetoglu, 2016; Wesche & Sonderegger, 2019). For example, General Electronics used an AI production boss (Click2Make) that could assign and manage work to humans based on a wide range of information, ranging from the employees’ skill sets to their physical traits (e.g., right/left-handedness) (Sahota, 2020). Another example is Metlife, which uses an AI manager for their call center, where the AI manager monitors the performance of each customer service representative and provides feedback (e.g., if the agent is not empathic toward the customer, the AI manager sends a “heart icon” to the employee) (Sahota, 2020). Also, Cogito, an AI-based manager developed by MIT Media Lab, has been used to supervise call center employees. While the human managers are limited in the number of employees that they can supervise, Cogito detects the employee’s emotions and speech patterns (using the NLP algorithm) in phone conversations in real time and provides suggestions for improving a call to the employees (Johnston, 2019).

Functionally, these recent deployments of the AI as a “boss” in the workplace have shown huge potential in increasing the efficiency and productivity of human employees. Nevertheless, the “AI manager” may be spurious since the “manager” title is not given explicitly to the AI as a self-presentation tactic within or outside the organization. As discussed earlier, the Heuristic Judgment Model explains that compared to the AI agent with the lower title such as the customer representative, a higher job title, “customer manager” as a heuristic cue can be seen to be more competent in such attributes as knowledgeability, trustworthiness, and likeability.

H2. The AI agent with the title “manager” will be perceived to be higher in terms of a) likeability, b) knowledgeability, and c) trustworthiness than the AI representative.

Further, following the same logic of the Heuristic Judgment Model, “promoting the AI agent” to the representative or the manager (i.e., the AI customer representative to the AI customer manager) can perceptually increase the efficacy of not only customer satisfaction (as discussed earlier) but also other marketing outcomes such as “brand attitude” and “purchase intention” via improving the favorable perceptions of the AI agent’s attributes, including likeability, knowledgeability, and trustworthiness (Chaiken, 1980; Clark, Wegener, Habashi, & Evans, 2012; Reinhard & Messner, 2009; Sinclair, Moore, Mark, Soldat, & Lavis, 2010). First, research suggests that the positive perceptions induced by highly evaluated attributes of the customer agents (i.e., high levels of likeability, knowledgeability, and trustworthiness) can have a carry-over effect on the evaluations of the agent (i.e., customer satisfaction) and the brand that the agent represents (i.e., brand attitude) because these positively evaluated attributes are highly or readily accessible as heuristics in consumers’ minds to influence these evaluations (Chaiken, 1980). Second, in terms of persuasive effect, the likeability of a message deliverer (e.g., the customer service agent) motivates higher elaboration of the persuasive message (i.e., the agent’s product recommendation), increasing the likelihood of purchasing the recommended product (Sinclair et al., 2010). Chaiken (1980) also explained that when a customer likes another person, the customer’s approach-oriented motive (i.e., wanting to find out the underlying message) is likely to be activated. That is, customers are more likely to explore and evaluate (i.e., approaching) the persuasive message given by likable or “approachable” agents and engage in the promoted behavior such as buying the recommended product (Reinhard & Messner, 2009). Third, the research found that the agent’s knowledgeability and trustworthiness are positively linked to the purchase intention (Clark, Wegener, Habashi, & Evans, 2012). Customers may find the information in the recommendation message as more “correct” and “valid” when delivered by a more knowledgeable or trustworthy agent. Based on these discussions, the current paper tested the following hypothesis:

H3. The positive perceptions (indicated by higher likeability, knowledgeability, or trustworthiness) of the AI agents will mediate the impact of the job title on a) customer satisfaction, b) brand attitude, c) purchase intention.

2.2.2. Transferring to the AI manager on the perceptions of the AI agents

Seeing the AI agents with job titles such as representative or manager *in isolation* is predicted to bring about favorable outcomes such as higher customer satisfaction. Yet, when assessing the impact of the job title "manager," one also needs to contextualize the effects of the job title in unique situations; customers interact with agents in higher positions only when they want to speak to staff members with higher positions, such as managers, anticipating better and more satisfactory handling of the issues at hand (Belbin, 2012; Salvaggio et al., 2007). Especially, when the customer is not satisfied with the frontline employee's performance, they are highly likely to want to speak to the manager or an employee with a higher position with the presumption that they can handle the situation better (Salvaggio et al., 2007). Also, in the real use case of Amazon, the AI agent is oftentimes located at the bottom of the hierarchy of customer support organization, where the human customer representative and the manager occupy the middle and upper positions, respectively (Amazon, 2021). In situations where the virtual (AI) agent is unable to solve the issues at hand, the customer resorts to the (human) customer manager, who has more power to make decisions, such as giving the customer compensations (Amazon, 2021). In this way, the customers are exposed to the relation between the representative and the manager. A common practice is when the AI agent is always seen first; then the customer is, by request, transferred to the agent with a higher position. However, if the agent is not human but AI, then the customers will be exposed to an unusual relation wherein the representative is human, and the manager is AI.

Regarding this phenomenon, two contrasting predictions can be made. On the one hand, an AI agent as a manager observed by customers to manage or supervise the human agents may lead customers to think that the AI agents are "capable" of managing human employees (Pronin, 2008). On the other hand, at a fundamental level, the unfavorable perception of the violation is expected due to humans' in-group bias (Steain, Stanton, & Stevens, 2019). An AI agent is an outgroup to the "human" group. The customers may feel uncomfortable or "threats to ingroup" seeing that the AI can be a manager or "boss" supervising its outgroup, human employees. Likewise, the customers may not "feel right" about humans "working with" rather than "using" AI representatives. This counterintuitive or uncomfortable relation between human and AI agents may have influenced the perception of the AI manager. For this reason, the expected positive effects of the AI manager will be weakened. However, to the best of the authors' knowledge, no direct theoretical and empirical explanations are available to clarify how the exposure to the "unusual" relationship between the AI and the human employee (the AI managing the human agents) can influence the customer perceptions of the AI agent. Although unusual, some companies (Amazon.com; transfer from AI-based "Amazon Assistant" that deals with general inquiries to AI-based "Seller Assistant" that deals with inquiries specific to specific sellers) already use the transfer between AI chatbots (rather than between an AI and human). An increasing number of studies have examined the AI-AI interactions (instead of human-AI interactions) because AI agents may be perceived differently depending on how they interact with other AI agents (Tan, Reig, Carter, & Steinfeld, 2019).

Due to the mixed predictions based on the literature review and the novelty of the phenomenon (AI agent shown to work with AI manager), instead of the hypothesis, the following research question is formulated and explored in the current study:

RQ: To what extent does the transfer from the human (or AI) representative to the AI (or human) manager influence the likeability of the AI manager?

3. Overview of experimental studies

Overall, across three studies, the current paper tested the hypotheses proposing a causal relationship between the job title and the perception of the AI agents and extended this model by examining the effect of the job title, via increased favorable perceptions of the AI agents, on the marketing outcomes (e.g., the intention to buy AI-recommended product). More specifically, Study 1 tested the effects of the job title on likability (H1), while Study 2 expanded this finding by testing the effects of the job titles on likability and two additional attributes (knowledgeability and trustworthiness) (H2). Additionally, Study 2 tested whether these attributes mediated the effects of job titles on the marketing outcomes including customer satisfaction, brand attitude, and purchase intention (H3). Study 3 extended Study 1 and 2 by answering the research question (RQ) regarding the effects of job titles in the context where customers are transferred from one agent (human or AI representatives) to the other agent (human or AI managers).

Study 1 used the scenario only while Study 2 and 3 used the combination of the scenario and the real chatbot. That is, across three studies, the current paper used both the scenario-only method and the combination of the scenario and the actual chatbot methods. Although scholars point out the high internal validity of the scenario method, the scenario has low external validity (Evans et al., 2015). Thus, Study 1 used the full scenario (vignette only) that provided detailed experiences (e.g., being a customer for a fictitious brand and chatting with an AI agent) that the participants were asked to imagine. In Study 2 and Study 3, the same scenario was used except the part of the scenario that asked the participants to imagine chatting with an agent for an actual brand. This part is replaced by the real AI agent (developed using an NLP algorithm) that was trained and used to replicate Study 1, increasing the external validity of the findings. In addition, across three studies, the current paper used three different scenarios to simulate the three most common uses of chatbots to increase the generalizability of the findings. In these scenarios, the participants: 1) complained [Study 1], 2) asked diverse questions [Study 2], 3) asked for detailed product information and recommendation [Study 3] (Drift, 2018).

4. Study 1

4.1. Method

4.1.1. Design and participants

One hundred thirty-eight individuals (female = 47.4%, *Mean* age = 38.98 [*SD* = 12.51]) recruited from Amazon Mechanical Turk participated in Study 1. According to a power analysis software G*Power (Faul, Erdfelder, Lang, & Buchner, 2007), our sample size was larger than the estimated sample size (72) needed to detect the effect size of 0.4 with β error rate of 0.15. The study takes about 4 min. Participants were paid $0.50. There were 22–24 participants in each cell of the 2 by 3 between-subject experimental design: agent (human vs. AI) × job title (no title vs. "representative" vs. "manager"). This online panel seems more appropriate than a laboratory study because the current studies aimed to better understand consumers' online interaction with the chatbot customer service.

4.1.2. Procedure and materials

The participants were instructed to imagine that they were customers for a fictitious brand, Chronotope Sportswear. They were also told to imagine going to the company website to chat with the customer service agent. For the "no title" condition, the conversation started with the agent saying, "Hello. I'm Michael, I am [an artificial-intelligence] customer service representative, working for Chronotope Sportswear. I will be assisting you today" (the manipulation for the human representative with no title). In the "manager" (or "representative") condition, the manipulations were done with the same greeting was used, except the agent said, "I am a customer service manager (or representative) for Chronotope Sportswear." The scenario depicted the same conversation about the size issue and the request for return. Then the conversation ended with the manager asking if there was anything else they could do to help. The full scenario can be found in Appendix A.

To measure the likeability of the agents, the five-item perceived likeability scale (Bartneck, Kulić, Croft, & Zoghbi, 2009) was used (*Mean* = 5.62, *SD* = 1.17, Cronbach α = 0.94). The participants rated the agent on a seven-point semantic differential scale (awful–nice, unpleasant–pleasant, dislike–like, unfriendly–friendly, and unkind–kind). Also, to minimize confusion coming from the individuals' difference in aptness in the simulation, the participants rated the easiness of the simulation on a seven-point Likert scale using a two-item perceived easiness of imagination scale ("It was easy for me to imagine what I was asked to imagine," "I was able to imagine what I was asked to imagine," *Mean* = 6.09, *SD* = 1.12, Cronbach α = 0.79).

4.2. Results

The first hypothesis posited that the likeability of the agents will be higher when presented with a job title (no title [control] vs. "representative" vs. "manager"). First, the simple main effect of the title was tested using one-way ANCOVA and found to be significant [F (2, 134) = 3.49, η2 = 0.05, p = .03]. The presentation of the title ("customer representative" or "manager") resulted in higher likeability (*Mean representative* = 5.78, SE = 0.16; *Mean manager* = 6.06, SE = 0.16) compared with the "no title" condition (*Mean no title* = 5.46, SE = 0.15) (p = .03). Thus, the first hypothesis (H1) was supported. Second, to test the interaction effect, data was submitted to 2 (agent: human, AI) × 3 (job title: no title, "representative," "manager") ANCOVA. The interaction was found to be significant [F (2, 131) = 3.31, η2 = 0.05, p = .03]. Planned contrasts using t-tests indicated that the AI manager was perceived to be significantly more likeable (*Mean AI-manager* = 6.37, SE = 0.23) than the AI representative (*Mean AI-representative* = 5.52, SE = 0.22) or the AI agent with no title (*Mean no title* = 5.62, SE = 0.21), (p = .03). However, no significant difference was found between the AI agent with no title and the AI representative, p = .74. Among the human agents, the difference between the representative and the manager was not significant (*Mean Human-representative* = 6.03, SE = 0.22 vs. *Mean Human-manager* = 5.79, SE = 0.21) (p = .43). Instead, the human representative was perceived to be significantly more likeable than the human agent with no title (*Mean Human-representative* = 6.03, SE = 0.22 vs. *Mean Human-no title* = 5.29, SE = 0.23) (p = .02; see Fig. 1 for the full visual description). In addition, the AI agents were compared with the human agents in their likeability scores using planned t-tests. The results showed that when no title was assigned, the difference in likeability between the AI agent and the human agent was not significant (p = .19). Also, there is no significant difference between the AI representative and the human representative (p = .104). However, the difference in perceived likeability between the AI manager and the human manager was (marginally) significant (*Mean AI-manager* = 6.37, SE = 0.23 vs. *Mean Human-manager* = 5.79, SE = 0.21) (p = .07). Overall, the results

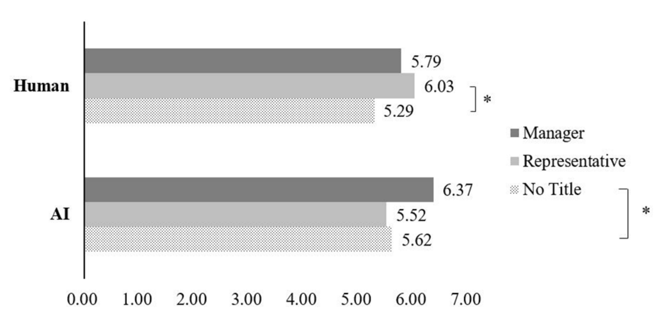

Fig. 1. Impacts of Job Titles on Perceived Likeability (Study 1). Note: *p < .05, **p < .01, ***p < .001.

in Study 1 provided initial evidence that the presence of the title improves the likeability of the AI agent.

5. Study 2

The major purpose of Study 2 is to replicate the findings in Study 1 in a more realistic setting using the real AI chatbot. Study 2 uses the AI chatbot platform developed for the current study. The AI chatbot is similar to the typical chatbots in functions and interface (see Fig. 5). This chatbot was developed with the NLP algorithm (derived from Python spaCy, CSS, JavaScript) that enables the bot to "talk with" the user about the products, the company, the services, or other related topics. When the user asks, for example, if he or she can customize Nike shoes for running, the chatbot can recognize and answer the question with the available information from the trained dataset. Also, Study 2 uses a real brand available in the markets, Nike, to increase the external validity of the findings of this paper (Lynch, 1982).

5.1. Methods

5.1.1. Training the AI chatbot

To train the chatbot to answer a wide range of questions that the customers might ask, the developers should first prepare the corpus of the questions and their answers (i.e., training datasets for supervised machine learning). Rather than instructing the participants to ask the chatbot questions prepared by the researchers, which can decrease the generalizability of the findings (Go & Sundar, 2019; Mullinix, Leeper, Druckman, & Freese, 2015), the researchers of this study let the participants freely ask the Nike AI agents anything that they wanted to ask. For this purpose, a survey was conducted to ask five hundred individuals recruited with the incentive of 50 cents (3-minute duration) from Amazon Mechanical Turk (female = 55.8%, *Mean* age = 37.57, *SD* = 13.27). In the survey, each worker came up with and typed ten questions that they would ask Nike as its customer. As a result, five thousand inputs were collected; after filtering out similar questions (using a text analysis software; Mladen, 2020) or non-questions that may have been mistakenly entered by the respondent (e.g., "is"), a total of 500 questions were extracted. In turn, the researchers searched for the most appropriate answers from Nike.com to those questions. For example, one of the most frequently asked questions was about the shipping policy (e.g., "How can I get free shipping on Nike?"). The bot then answered the question by saying, "Of course, we offer free shipping! Let me give you more details: 1. Standard (12–16 business days for orders placed by 5:00p.m. EST) […]" This answer was an edited version of the answers originally found in Nike Help (https://www.nike.com/help/a/returns-policy). If the question cannot be answered by the bot from the pool of available data, then the bot offers the "default" answer that tells the participants that they can visit Nike.com for more information. In Study 2, no default answer was triggered as the bot was able to answer all the questions. The chatbot was trained with the extracted questions and their answers by importing them into its server. The chatbot was then programmed with a matching algorithm that enabled it to match only the keywords from the questions (excluding stop words such as "the" and "a") with relevant answers from the pool. Lastly, the chatbot layout was designed in a simple way, just like Nike's design (Fig. 5). To minimize confusion with regard to the difference between the contents of the conversation with the AI representative and that with the AI manager, the researchers examined the question topics and conversation duration and found that none of the factors significantly interacted with the independent variable (job title) on any of the dependent variables.

5.1.2. Design and participants

Sixty individuals (female = 38.46%, *Mean* age = 37.58 [*SD* = 11.42]) from Amazon Mechanical Turk participated in Study 2 in return to the monetary incentive ($0.60). The sample size was sufficient to detect the effect size of 0.4 with β error rate of 0.15.

The study takes about 6 min to complete. They were randomly assigned to either the AI representative chatbot (n = 29) or the AI manager chatbot (n = 31).

5.1.3. Procedure and materials

Study 2 used a real chatbot. Yet, it is still necessary to establish the contexts providing the reasons why participants may get to chat with the customer service employees. Therefore, before actually interacting with the chatbot, all the participants were instructed to imagine that they are a customer who is interested in asking the questions for the sportswear brand, Nike (see Appendix A). Thus, Study 2 combines the mental simulation (scenario) with the real interaction with the chatbot. Also, for this reason, the same covariate for the easiness of the imagination was used in the analyses of the results. The same manipulations for the agents with different job titles (the greetings with the statements revealing who they are) that were used in Study 1 was used for Study 2. They were also instructed to talk to the customer service agent for Nike on the online chat platform. The participants were told that they could ask any questions that they would ask Nike as customers for the brand. To chat with the agent, each participant clicked the link that directed them to the chat platform. If the participant clicked the link, a new browser window for the chat platform popped up. They were told to chat with the bot for no longer than five minutes, and then they were told to return to and finish the survey. Also, on the chat platform, if the chat duration reached five minutes, the bot said, “Thanks for chatting with me,” and the chat platform automatically closed. The same scale for measuring perceived likeability was used (α = 0.97, mean = 4.88, SD = 1.73). In addition, perceived trustworthiness and knowledgeability were measured using a four-item binary scale (“dependable”–“undependable,” “honest”–“dishonest,” “sincere”–“insincere,” “trustworthy”–“untrustworthy”; α = 0.93, *Mean* = 3.07, *SD* = 1.24) (Ohanian, 1990) and a five-item binary scale (“ignorant”–“knowledgeable,” “unintelligent”–“intelligent,” “incompetent”–“competent,” “foolish”–“sensible,” “irresponsible”–“responsible”; α = 0.96, *Mean* = 4.75, *SD* = 1.71) (Ho & MacDorman, 2010), respectively. The satisfaction with the customer service provided by the manager was measured by asking participants to indicate to what extent they agree with the 3 items: “I was [content/pleased/happy] with Michael’s service” on a 7-point scale (1 = not at all to 7 = very much), α = 0.97, *Mean* = 4.59, *SD* = 2.09 (Hyun, 2010). Participants rated their attitude toward the brand (bad–good, unpleasant–pleasant, unfavorable–favorable, α = 0.92, Mean = 5.502, SD = 1.43), and their intention to purchase the product of the brand (unlikely/improbable/impossible, α = 0.93, Mean = 4.514, SD = 1.75) on two separate three-item bipolar scales (MacKenzie & Lutz, 1989).

5.2. Results

First, the data was submitted to MANCOVA to examine the impact of the AI agent’s job title (“representative” vs. “manager”) on likeability, knowledgeability, and trustworthiness, with the easiness of imagination (*Mean* = 5.12, *SD* = 1.16, α = 0.73) entered as a covariate. The results showed a significant difference in likeability, knowledgeability, and trustfulness [F (3, 55) = 12.96, $p < .001$, Wilks’ Λ = 0.59, η2 = 0.41]. The AI manager was perceived to be better than the AI representative in terms of likeability (*Mean AI-manager* = 5.76 [SE = 0.23] vs. *Mean AI-representative* = 3.94 [SE = 0.24]; $p < .001$), knowledgeability (*Mean AI-manager* = 5.67 [SE = 0.23] vs. *Mean AI-representative* = 3.78 [SE = 0.23]; $p < .001$), and trustworthiness (*Mean AI-manager* = 3.35 [SE = 1.96] vs. *Mean AI-representative* = 2.76 [SE = 0.202]; $p = .04$). Thus, H2 was supported. The detailed visual depictions of the results can be seen in Fig. 2. Next, a series of moderated mediation analysis with the multiple mediators (likeability, knowledgeability, and trustworthiness) and multiple outcomes (customer satisfaction, brand attitude, and purchase intention) were performed (Hayes PROCESS Macro Model 4, Bootstrapping = 5,000; Hayes, 2017). The results showed that only perceived likeability significantly mediated the impact of the AI agent’s job title on 1) customer satisfaction (B = 0.66, 0.28 < CI < 1.04), 2) brand attitude (B = 0.35, 0.07 < CI < 0.62), 3) purchase intention (B = 0.38, 0.08 < CI < 0.67), while knowledgeability and trustworthiness did not significantly influence any of the marketing outcomes as their confidence intervals include zero. Thus, H3 was supported only in the case of the likeability on the marketing outcomes. In conclusion, the result from Study 1 that the perceived likeability of the AI “manager” was higher than that of the AI “representative” was replicated in a more realistic setting, with the real chatbot trained as an AI agent for Nike. In addition, as expected, the job title influenced the perceptions of knowledgeability and trustworthiness, yet only likeability significantly improved customer satisfaction. A full visual description of the model results can be seen in Fig. 3A.

6. Study 3

Study 3 is designed to replicate the results of Study 2 in a typical situation of customer service where customers first encounter the representative (human or AI) and then transferred to the manager (human or AI). In so doing, Study 3 examines to what extent the hierarchical relation between AI as and human influence the perception of the AI manager. Further, Study 3 expands from Study 2 by testing the mediating impact of the positive perception of the AI manager on not only customer satisfaction but also brand attitude and intention to purchase the product recommended by the AI manager. In Study 3, there is one technical update on the platform. To mimic the speed of human typing on the chat, the chat platform’s replies were deliberately delayed

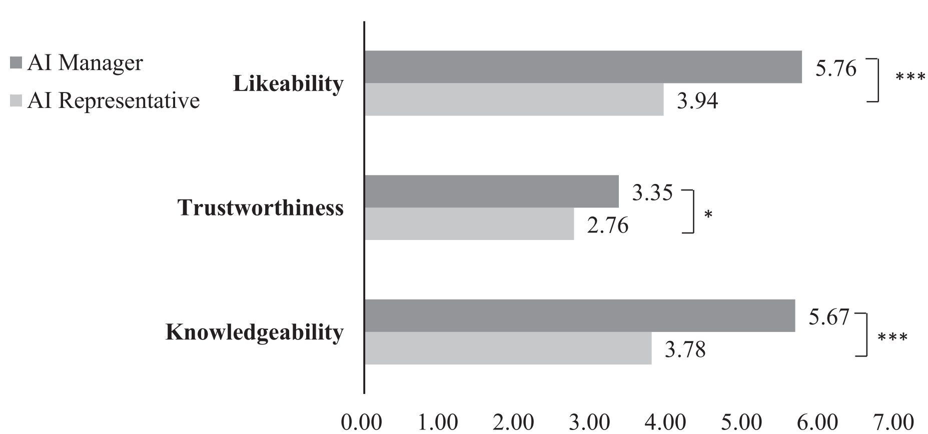

Fig. 2. Impacts of Job Titles on Perceived Likeability, Trustworthiness, and Knowledgeability (Study 2). Note: *$p < .05$, **$p < .01$, ***$p < .001$.

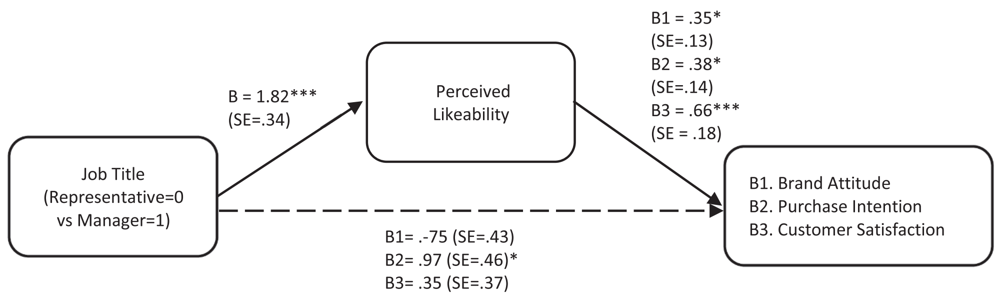

Fig. 3A. Mediation Analysis Result for Study 2. Note: *$p < .05$, **$p < .01$, ***$p < .001$. B refers to unstandardized beta coefficient. SE refers to Standard Error.

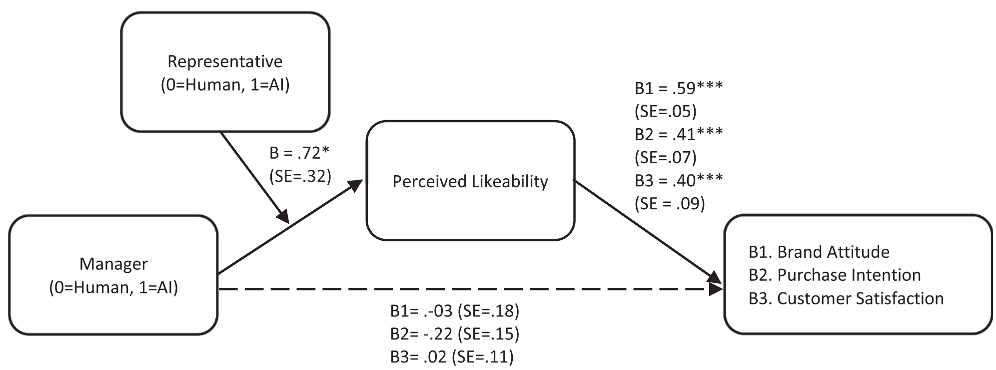

Fig. 3B. Mediation Analysis Result for Study 3. Note: B1-B3 refers to unstandardized beta coefficients for Brand Attitude, Purchase Intention, and Customer Satisfaction respectively. SE refers to Standard Error.

in proportion to the word counts of the replies. This technical update will make the response more natural or human-like (instead of the chatbot giving the answer in a split-second) help the manipulation of the chatbot that will pretend to be “human” representative and manager in our experiment (Jurczyk, 2018).

6.1. Methods

6.1.1. Design and participants

One hundred seventy-seven individuals (female = 51.07%, *Mean* age = 37.29 [*SD* = 12.43]) recruited with the monetary incentive ($0.60) from Amazon Mechanical Turk participated in Study 3 that takes about 6 min. Some participants who had chatted with the human agents may have suspected or thought that the agents were not human but AI since the “human” agents (which were, in fact, bots) did not introduce themselves as “human” customer service employees. Thus, to check whether this is the case, after the chat, the participants were asked to indicate whether the agent was AI. Seventeen participants were excluded because they had answered that the “human” representative was AI, while nineteen participants were excluded because they had answered that the “human” manager agents were AI. Of those, 6 participants were wrong on both questions. Thus, the resulting sample size was 147 (which was sufficient to detect the effect size of 0.4 with β error rate of 0.05), with 31–42 participants per cell in the 2 representative (human vs. AI) × 2 manager (human vs. AI) experimental design. The experimental manipulation for the transfer from the customer representative to the customer manager on the real chat platform will be further explained as follows.

6.1.2. Procedure and materials

The same chat platform as that used in Study 2 was used. Also, the general procedure is similar to that of Study 2 except the situation wherein the customers are transferred from one agent (the representative) to the other (the manager). To construct this situation, first, participants were instructed to imagine that they are interested in asking a question about the shoes for overpronators (people with wide feet) on the online chat (see Appendix A). Then, the participants started the conversation with the customer service representative (human vs. AI) on the chat platform. Then, as instructed, they asked the representative on the chat platform if they could recommend products for overpronators. The participants could ask the same question in their own ways (e.g., “Can you recommend items for overpronators?”, “I need shoes for overpronation,” “Do you have shoes for wide feet?”) on the platform as the platform can extract the meanings of the questions from the keywords related to overpronation. However, the participants were pre-instructed not to engage in conversations about other unrelated topics. All the participants in Study 3 strictly followed the instructions and did not deviate from the topic of the conversation. Then to minimize confusion from different ways of answering the same questions across all the human and AI conditions, all the agents responded to all the participants with the same answers: “Generally, our shoes are designed to provide maximum comfort to feet. And if you want to discuss our products specifically designed for overpronators, our manager can better assist you in that respect. Do you want to talk with our manager instead?” As pre-instructed, the participants indicated that they want to be transferred to the manager by saying, “Yes,” “Sure,” or other similar words. In turn, the representative said, “Then I will transfer you to our customer service manager. Please wait until he joins you in the chat. Thank you for your patience.” The agent provided a button (“Click Here”) that directed the participants to a new chat window with the manager. Then the manager joined the conversation and greeted the participants. The participants asked the manager the same question, and then the manager recommended a product for overpronators with an explanation as to why the product was good for overpronators (e.g., “It has lightweight foam cushioning”). Then, the manager recommended a pair of shoes designed for overpronators to the participants on the chat platform. Lastly, the conversation ended with the manager saying, “Please check out the shoes and get back to us if you have any other questions!” The participants returned to and finished the survey.

The same likeability (α = 0.95, mean = 5.97, SD = 1.07) and customer satisfaction (α = 0.92, mean = 6.21, SD = 0.94) scales were used. The carry-over effects of the likeability of the AI on the core marketing outcomes using the same scales used for Study 2 including brand attitude (α = 0.94, *Mean* = 5.97, *SD* = 1.07), and intention to purchase the product (the running shoes recommended by the AI manager by the end of the conversation during the chat) (α = 0.89, *Mean* = 5.72, *SD* = 1.16) (MacKenzie & Lutz, 1989).

6.2. Result

To answer the proposed RQ regarding the impacts of different pairings of AI-human agents, the data was submitted to 2 (representative: human, AI) × 2 (manager: human, AI) ANCOVA. The results showed that the interaction was significant, $F(1, 142) = 4.92$, $p = .02$, η2 = 0.03. Planned contrasts using t-tests indicated that the likeability of the AI manager was significantly higher when they were paired with the AI representative than with the human representative (*Mean AI rep → AI manager* = 6.25, SE = 0.17 vs. *Mean Human rep → AI manager* = 5.68, SE = 0.15) (p = .03). However, there was no significant difference in the likeability of the human manager between being paired with the human representative (*Mean* = 6.17, *SE* = 0.16) and being paired with the AI representative (*Mean* = 6.02, *SE* = 0.15) (p = .32). Further, the current research compared the typical order (seeing the AI representative first and then the human manager) with the opposite order (seeing the human agent first and then the AI manager), and found no significant difference, (*Mean AI rep → Human manager* = 6.02, SE = 0.16 vs. *Mean Human rep → AI manager* = 5.68, SE = 0.15), p = .12. Thus, the likeability of the manager was higher when customer was transferred from the AI representative to the AI manager than when customer was transferred from the AI representative to the human manager (see Fig. 4 for the full details). The overall results suggest that the likeability of the AI being the manager depends on the different pairings of human and AI agents. Lastly, to test H3, three moderated mediation analyses (PROCESS Macro Model 7, 5,000 bootstrapping samples) (Hayes, 2017) were conducted to examine the carry-over effects of perceived likeability on customer satisfaction, brand attitude, and sales persuasion by the AI manager. The first analysis showed that the moderated mediation model was significant (index of moderated mediation = 0.42, 0.07 < CI < 0.83). The interaction coefficient on perceived likeability within the model was significant (B = 0.72, *SE* = 0.32, *t* = 2.21, 0.07 < CI < 1.35); in turn, the higher the perceived likeability, the higher the customer satisfaction (B = 0.59, 0.47 < CI < 0.70). The second and third analyses also showed that the higher the perceived likeability, the higher the intention to buy the recommended product (B = 0.41, 0.25 < CI < 0.57), and the better the attitude toward the brand (B = 0.40, 0.21 < CI < 0.58). All in all, perceived likeability that was interactively influenced

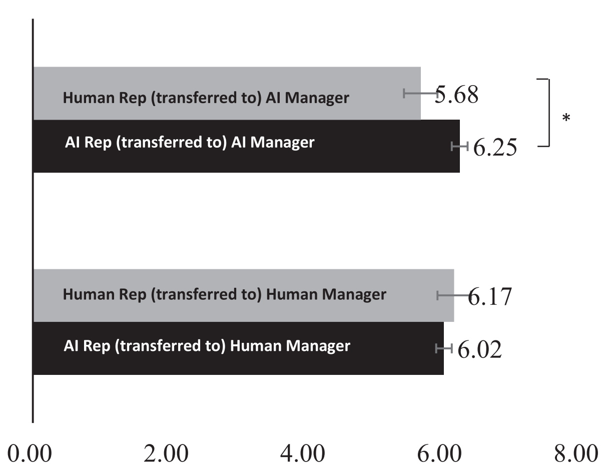

Fig. 4. Perceived Likeability of AI manager. Note: *p < .05, **p < .01, ***p < .001.

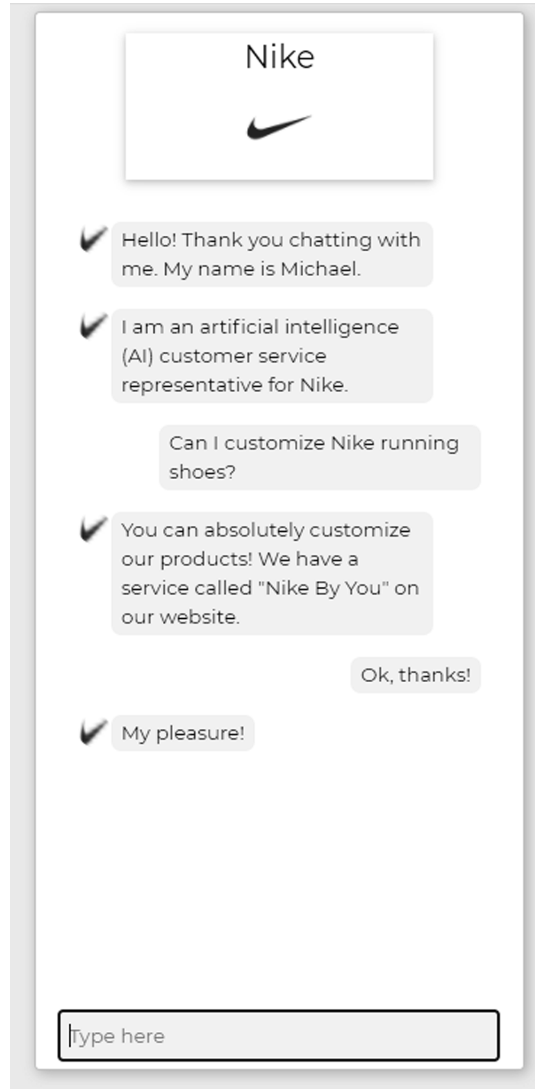

Fig. 5. The AI chatbot platform used for Studies 2 and 3. Note: the above image shows a conversation occured between the AI agent (the chatbot) and a study participant in the chat platform developed for the current studies.

by the agent and the job title had carry-over effects on the marketing outcomes of the chat with the AI manager (Fig. 3B).

7. General discussion

The speed at which AI is transforming business is at an unprecedented high (Davenport et al., 2020; Kurzweil, 2005). Particularly, AI applications such as the AI chatbot have already been widely used in customer service, reducing costs and increasing efficiency for customer relation marketing (McLeay et al., 2021; Pantano & Pizzi, 2020; Vlačić et al., 2021; Xiao & Kumar, 2019). Nevertheless, customers have unfavorable perceptions of AI agents, which can result in the reduction of the efficacy of AI-driven marketing strategies. Thus, in response to such limitations of using AI in business, scholars have been researching ways that optimize marketing tactics using AI technologies (Adam et al., 2020; Davenport et al., 2020; Granulo et al., 2021; Grewal, Guha, Satornino, & Schweiger, 2021; Huang & Rust, 2021; McLeay et al., 2021). Nevertheless, such scholars have called for more research that provides a wider range of practical inputs in strategically using AI in business contexts (Loureiro, Guerreiro, & Tussyadiah, 2021). In response, this study contributes to the previous literature on AI in marketing by testing a novel marketing tactic that utilizes an AI chatbot. Previous research has suggested various ways to increase the efficacy of AI agents, such as the use of profile pictures (Go & Sundar, 2019; Lv et al., 2021) or conversational styles (Adam et al., 2020; Go & Sundar, 2019), expressing emotions (Czerwinski et al., 2021), or finding relevant business contexts for AI use (Granulo et al., 2021).

In addition to previous findings, this study provides evidence for a simple but effective tactic that can increase the efficacy in using AI agents for marketing: assigning human job titles to AI agents. The study proposed and tested this tactic based on the theoretical understandings of how humans judge an AI agent based on heuristic cues (Kahneman, 2011). A previous study on AI agents suggested that humans are likely to perceive AI agents as social beings instead of cold machines (Nass & Lee, 2001). Following this approach, it is predicted that the psychological models designed for and applied to understanding human perception can help us understand "machine perception" (Kahneman, 2011). Accordingly, this paper proposed and supported the marketing tactic of using the *job title* as a simple perceptual cue that enhances the favorable perception of AI agents. Also, this paper provides empirical evidence that the change of such a simple cue can enhance various AI-driven marketing outcomes, such as higher customer satisfaction, a more favorable brand attitude, and a stronger intention to buy AI-recommended products. More importantly, the paper shows the feasibility of assigning a higher human job position such as "manager" to an AI agent. This finding contributes to the current academic and industry discussions of the "AI manager" or "AI boss" in the business context (Sahota, 2020; Chamorro-Premuzic & Ahmetoglu, 2016), which still lacks direct empirical evidence on to what extent and how the AI manager is useful for boosting business outcomes. In particular, this study shows "when" the manager-level job title assigned to the AI agent will result in favorable or unfavorable outcomes. Moreover, this study examines the AI chatbot in situations where customers first get to chat with a "middleman" agent (which is often an AI), followed by chatting with the main human or AI agent. This phenomenon is common in online customer chat services (Amazon 2021) yet receives little academic attention. Thus, this paper fills in this research gap by answering the research questions regarding to what extent the hierarchical relation between the AI agent and the human agent or between AI agents complicates the perceptual influences of the job titles assigned to AI agents on marketing outcomes. We provide the theoretical and practical implications of the findings as follows.

7.1. Theoretical contributions and implications

Overall, this study contributes to the literature on the human models of robot perceptions or the robot models of human perceptions in business contexts (Murphy, 2019). Particularly, it employed the cognitive bias model, Heuristic Judgment Model, to explain the human perceptions of non-human/AI agents (Chaiken, 1980; Lim, Benbasat, & Ward, 2000). The cognitive biases toward the human perception can be, as evidenced in this study, applicable to non-human or AI employees. Adding to the evidence for the CASA paradigm (Nass & Lee, 2001), this study showed that humans perceive the robot as just another social being whose perceptions shift depending on a simple heuristic cue: a job title. Further, the current study supports the carry-over or "halo" impacts of the heuristic cue (Chaiken, 1980; Clark, Wegener, Habashi, & Evans, 2012; Reinhard & Messner, 2009; Sinclair et al., 2010) on the marketing efforts such as the product recommendation made by AI agents. This also suggests that the favorable effects of the heuristic cues can be observed not only with humans but also non-human agent (e.g., AI agent).

Moreover, the current study also suggests that such a positive effect predicted by the theoretical model for the person perception cannot fully explain the robot perception. What is somehow unique and unexplained by previous studies is that the impact of the heuristic cue can be moderated (i.e., mitigated or enhanced) by hierarchical relations between human and robot or AI agent (i.e., AI being a manager to a human representative). The positive impact of the manager-level job title was observed when consumers chat with AI manager in isolation; however, in the situation when consumers get to talk with the customer representative and the manger *in sequence*, the results flipped. That is, consumers perceived the AI manager more favorably when they were transferred from the AI representative as compared to when they were transferred from the human representative. This result supports the prediction that when contextualized in the AI-human relation, customers may still not want the customer representatives to be "supervised" by robot bosses, which are "out-group" or non-humans (Granulo et al., 2021). This weighs in one of the contrasting views (i.e., ingroup bias) discussed in the current paper: individuals would not feel comfortable to see their in-group (humans) are "managed" by their out-group. This finding, however, still remains explorative and needs future studies to test the psychological mechanism of the in-group bias using a proper operationalization of the perceived threat to ingroup distinctiveness that applies to human-robot or robot-robot relation (Fraune, 2020).

7.2. Implications for practice

Scholars called for research that provide the practical inputs in strategically using AI in business contexts (Loureiro et al., 2021). In response, the current study provides the following managerial implications. Firstly, since customers have more favorable perceptions of the AI manager (which result in various positive marketing outcomes), the business owners can consider "promoting" the AI agents to the manager position. This tactic or business decision is cost-efficient because the AI manager agents would not "ask for raise in salary." Also, in terms of implementation costs, the current pricing trend shows that the advancements of the AI technologies as well as soaring number of the chatbot venders are likely to reduce the costs of the chatbot implementations further (Insider, 2021). Certainly, assigning a job title to too many unqualified employees may be unjust and result in "title inflation" (Martinez et al., 2008), yet the current advancement of AI technologies can equip the AI agent with the capability of doing customer service tasks more efficiently and faster than their human counterparts (Pantano & Pizzi, 2020). The current practices of deploying AI agents with no specific or ambiguous titles assigned to them (e.g., "virtual agent" or "customer service chatbot") may further "hide" their capabilities from customers. The findings across the three studies suggest that customers have more positive impressions (more likeable, more trustworthy, and more knowledgeable) of the AI agent with the title "customer manager" than the AI representative or the agents with no title. The customers may get the impression that the AI agents have skill sets or qualifications that they would expect from typical "managers." Note that the positive impact of giving the AI such a senior job title as "manager" would backfire if the AI agents are not perceived or expected to fit the job (Venkatesh & Goyal, 2010). However, the findings in this study showed that the "promotion to manager" enhanced the favorable perceptions of the AI agents. Further, they suggested that the increased likeability of the AI agents can lead to increased customer satisfaction, better brand attitudes, and the higher likelihood of purchasing the products recommended during the chat by the AI agents. In other words, the simple tactic of giving appropriate titles to AI agents can result in a series of positive and noteworthy marketing outcomes.

Secondly, the customers perceived the AI manager more positively when they were transferred from the AI representative to the AI manager than from the human representative. This finding has strong implications for the current tactics of using AI agents on company websites. Typically, in online malls such as Amazon, the AI agent is used as the frontline "gate" (Amazon, 2021). Only when the customers insist on being connected with "human" agents do they get to talk with human representatives or managers. Thus, the typical industry practice is that the customers first encounter the AI agent before they are transferred to the human agent. This study compared this order with the opposite order or the different pairing: customers seeing the human (or AI) representative first and then seeing the AI manager. The results showed that the AI manager was perceived to be more likeable when it was teamed up with the AI representative rather than the human representative while the typical pairing (the AI representative-human manager) did not differ from the human representative-AI manager pairing. Thus, when deploying AI managers, the business owners should consider optimal pairings of the AI and human employees. One might argue that the same algorithms with different naming (i.e., title) may not be useful and unnecessary since they can offer the same capacities (e.g., the same level of language processing, the same capacity of information processing, etc.). However, dividing the same workforce with the same capabilities can be a psychological *tactic*, namely, "compartmentalization" (Amiot, Louis, Bourdeau, & Maalouf, 2017). Compartmentalization generally refers to the division of the self-identity into different sub-identities that are separate from each other (Amiot et al., 2017). Previously applied to humans, this concept can be useful for the robots because the different sub-identities of the same robot can differently serve the consumers depending on their goals and needs. If the agent with no title or the title of "customer representative" tries to respond to consumers with a question that the manager can handle, consumers may experience the dissonance between their goals and the responses for the AI agents who are incongruent with what they need or want. Surely, however, future studies need to be conducted to examine to what extent the cognitive mechanism of the compartmentalization is at work along with other competing explanatory factors such as the in-group favoritisms. Instead, the result of our studies provided first evidence of "compartmentalization of AI agents" that can boost the customer's positive perception of the AI agents, which subsequently resulted in favorable marketing outcomes.

Also, the current AI technologies may still not be advanced enough for the AI agents to take more sophisticated human abilities such as emotional or "empathetic intelligence" (Huang & Rust, 2021). So, giving the manager title to the AI agents can result in positive perceptions and business outcomes; but at the same time, the AI agents may not be apt at handling other roles such as understanding customer/employee emotions and mitigating their complaints. However, the artificial intelligence, specifically natural language processing (NLP), is one of the fastest advancing areas (Huang & Rust, 2021), and scholars and industry experts foresee the AI agents with strong emotional intelligence. Indeed, much advanced AI agents with sophisticated human abilities that will fulfill the manager's such sophisticated roles as understanding and responding to customer emotions will be available in the market in no time (Czerwinski, Hernandez, & McDuff, 2021). Scholars then may need delve into how those technologies will be perceived and used from the customer perspective.

7.3. Limitations and future research direction

This study has several limitations. First, the findings are limited to a chatbot for sportswear brands. Customer service jobs may differ across different product categories, such as food, electric appliances, health care, beauty, and interior design. One study found that consumers prefer human employees in symbolic consumption contexts (e.g., designing offices), while they prefer robot workers in less symbolic contexts, such as educating patients (Granulo et al., 2021). This shows that customers' perceptions and expectations of the same job (e.g., manager) can differ across different product or service categories. For example, customers may prefer AI agents for informational services, such as pension counselling, rather than services that involve aesthetic skills, such as fashion consulting. A recent study, for example, showed that without knowledge of the tasks given to a person, the person prefers to get advice for the task from human agents, but when the task is known (e.g., arithmetic calculation or understanding emotion), depending on the tasks, the person prefers advice from the AI (Hertz & Wiese, 2019)—that is, none of the kinds of agents (human or AI agents) are seen to always excel in the given task. This may explain one of our findings that the AI customer service manager tends to be seen as more likeable than the human agent with the same title. In the study, the AI manager's job was to accurately provide correct information. As an "algorithm" run on a computer server, the AI manager may have been seen as better for the given job. However, if the job was done in a different context, where the AI agents need to understand nuanced or sophisticated emotional or creative goals (e.g., mental therapy services or beauty service inquiries), the finding could be reversed (e.g., the human manager is seen as more capable and skilled than the AI manager) (Rampersad, 2020). This is another area that future studies can examine to provide useful inputs for different service areas or contexts.

Second, this study used a chatbot in controlled online experiments. This way, the authors of the study attempted to induce a situation wherein the customers interact with the service employees. The conversation between the participant and the AI chatbot was unscripted in Study 2 (where the participants freely asked any question about the product) and scripted in Study 3 (where the participants asked the chatbot certain questions). Nevertheless, it is desirable to test whether the findings from the experimental studies can be held with the real-world data via field or natural experiments.

Third, other than the perceived easiness of the imagination, this studies did not control for other potentially influential factors such as preexisting attitudes toward the brand (Zarouali et al., 2018) or familiarity with AI technology (Dash & Bakshi, 2019). For instance, the participants from the online panel may be more familiar with online technologies, including the AI chatbot, and the more familiar people are with the AI chatbot, the more favorable their perceptions of the AI chatbot are (Dash & Bakshi, 2019; Vlačić et al., 2021). Hence, to increase the generalizability of the findings, we suggest including those control variables in future studies that examine AI customer service agents.

Lastly, the studies did not answer the potential research question on the extent to which customers would perceive AI managers or representatives if these agents did not satisfy their needs. Across all the studies—including Studies 2 and 3, which used real chatbots—the AI agents fulfilled the customers' needs (answering the questions) using the training data from the chatbot's server. However, the favorable effect of the job titles may diminish or remain intact when the AI agents do not do their jobs well. This may explain the non-significant effects of knowledgeability and trustworthiness in Study 2 on marketing outcomes. To see stronger influences of those *perceived* attributes on marketing outcomes, the agents may need to prove, via fulfilling the customers' goals and needs, that they are more knowledgeable and more trustworthy (e.g., talking about product details, more conversations to show that they are trustworthy). More specifically, given that both human and AI agents can fail to meet the customers' needs, future studies may benefit from exploring how the AI agents should handle the situation when things go wrong with the customers, just as human agents would (e.g., apologizing and attributing the issues to themselves), or the AI agents, unlike the human agents, can have other tactics to deal with the situation (e.g., apologizing and attributing the issues to the company or the AI developers).

Despite the abovementioned limitations that need to be overcome in future studies, this paper explores and provides novel evidence regarding a simple but effective tactic of using AI technology to enhance customer service satisfaction. The study contributes to the literature on the strategic uses of AI in managerial roles in business contexts. Based on these findings, therefore, future studies need to further theoretically and empirically examine the best ways of using emerging and fast-advancing AI technologies in different business contexts.

8. Conclusions

The results across the three studies shed light on how the AI agent's self-presentation tactic using higher level job titles such as manager can boost marketing outcomes. The results of the current paper indicate that the favorable perceptions of the AI agents can be induced by the job titles as a heuristic cue or "professional identity badge". At the same time, the results of this study point to the fact that compared to human service employees, "AI service employees" should be deployed in a different way—that is, the positive perception of the AI manager was contingent on whom the AI manager was seen to be paired with (the human representative versus the AI representative). In conclusion, this study shows that marketers and scholars need to come up with innovative marketing tactics that keep up with the development of AI tools such as the chatbot that show new levels of technological sophistication, which requires "AI-specific" marketing tactics to best utilize the technologies.

CRediT authorship contribution statement

Yongwoog "Andy" Jeon: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The author would like to thank the Editors and reviewers of the Journal for their insightful and constructive comments on earlier versions of the manuscript.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Scenarios for Study 1 and 2

Scenario for Study 1	Scenario for Study 2
Instruction: Imagine that you are a customer for the sportswear brand named Chronotope Sportswear and you recently bought shoes from the brand's online store. But, the shoes do not fit your feet properly, and you found that the sizes of the shoes that you received are not those that you chose in the online store. So, you decide to go to the company website to use the online chat service. You click on the online chat icon located on the bottom right corner of the webpage. Please wait til the next button appears. Then click the next button to proceed. *The chat has started.* **Michael:** Hello, Chris! I'm Michael. I am [an artificial-intelligence customer service representative,] working for Chronotope Sportwear. **Michael:** I will be assisting you today. **Chris | Customer:** Why did I receive the wrong size of my shoes? **Michael:** We're very sorry about your recent purchase. It is our mistake that we sent you the wrong-sized pair of shoes. **Michael:** If you'd like, we will send you a replacement. Or if you prefer, we will refund your purchase. **Chris | Customer:** I'd like to receive the replacement. How long does it take to receive the replacement? **Michael:** Due to the popularity of the shoes that you purchased, the product is currently out of stock. **Michael:** We're expecting to have them in stock in 2 weeks. Then it will take 7 to 14 business days to deliver the product to you. **Chris | Customer:** Four weeks? That's a long time … But I still want it. Please go ahead and process the replacement. **Michael:** Again, we're very sorry to cause this trouble. Is there any other thing that I can help with today? **Chris | Customer:** No, that's it. **Michael:** Thank you for using our service today. Have a wonderful day! *The chat is closed.* Note: For all the six experimental conditions in Study1, the same scenario as can be seen above was used except the self-introductions in the blanket: for the AI conditions, 1) artificial intelligence (AI) customer service representative, 2) artificial intelligence (AI) customer service manager, 3) artificial intelligence (AI) chatbot. For the human conditions, the same job titles were uttered without "artificial intelligence (AI)" except the condition for the human agent with no title where the part in the blank was not uttered.	**Instruction:** Imagine that you are a customer for the sportswear brand, Nike. On the company website, you found an online chat for the customer service. You are interested to ask some questions on the online chat. Now, you will be provided with a link to the Nike chat service. Please wait til the next button appears. Then click the next button to proceed. Note: Once participants click the next button, the link for the chatbot appeared. When participants click the link, a window for the chatbot popped up (see Fig. 5). Scenario for Study 3 **Instruction:** Imagine that you are a customer for the sportswear brand, Nike. On the company website, you found an online chat for the customer service. You are interested to ask some questions about the shoes for overpronators (people with wide feet) on the online chat. Now, you will be provided with a link to the Nike chat service. Please wait til the next button appears. Then click the next button to proceed.

References

Adam, M., Wessel, M., & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 1–19.

Ahearne, M., Mathieu, J., & Rapp, A. (2005). To empower or not to empower your sales force? An empirical examination of the influence of leadership empowerment behavior on customer satisfaction and performance. *Journal of Applied Psychology, 90*(5), 945.

Amazon. (2021). *Amazon Customer Service*. Retrieved from https://www.amazon.jobs/en/business_categories/amazon-customer-service. Accessed 5 April 2021.

Amiot, C. E., Louis, W. R., Bourdeau, S., & Maalouf, O. (2017). Can harmful intergroup behaviors truly represent the self?: The impact of harmful and prosocial normative behaviors on intra-individual conflict and compartmentalization. *Self and Identity, 16*(6), 703–731.

Ansoff, H. I., Kipley, D., Lewis, A., Helm-Stevens, R., & Ansoff, R. (2018). *Implanting strategic management*. New York, NY: Palgrave Macmillan.

Baron, J. N., & Bielby, W. T. (1986). The proliferation of job titles in organizations. *Administrative Science Quarterly, 31*(4), 561–586.

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics, 1*(1), 71–81.

Belbin, R. M. (2012). *Team roles at work*. New York, NY: Routledge.
Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology, 39*(5), 752–766.
Chaiken, S., & Maheswaran, D. (1994). Heuristic processing can bias systematic processing: Effects of source credibility, argument ambiguity, and task importance on attitude judgment. *Journal of Personality and Social Psychology, 66*(3), 460–473.
Chamorro-Premuzic, T., & Ahmetoglu, G. (2016). The pros and cons of robot managers. *Harvard Business Review*. https://hbr.org/2016/12/the-pros-and-cons-of-robot-managers. Accessed 5 April 2021.
Clark, J. K., Wegener, D. T., Habashi, M. M., & Evans, A. T. (2012). Source expertise and persuasion: The effects of perceived opposition or support on message scrutiny. *Personality and Social Psychology Bulletin, 38*(1), 90–100.
Czerwinski, M., Hernandez, J., & McDuff, D. (2021). Building an AI That Feels: AI systems with emotional intelligence could learn faster and be more helpful. *IEEE Spectrum, 58*(5), 32–38.
Dash, M., & Bakshi, S. (2019). An exploratory study of customer perceptions of usage of chatbots in the hospitality industry. *International Journal on Customer Relations, 7*(2), 27.
Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42.
Dagger, T. S., Danaher, P. J., Sweeney, J. C., & McColl-Kennedy, J. R. (2013). Selective halo effects arising from improving the interpersonal skills of frontline employees. *Journal of Service Research, 16*(4), 488–502.
Elliot, C. (2018). *Chatbots Are Killing Customer Service. Here's Why*. April 27, 2018. https://www.forbes.com/sites/christopherelliott/2018/08/27/chatbots-are-killing-customer-service-heres-why/?sh=5f6b92cf13c5. Accessed April 5, 2021.
Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods, 39*(2), 175–191.
Fiske, S. T., & Taylor, S. E. (1991). *Social cognition*. New York, NY: Mcgraw-Hill Book Company.
Fraune, M. R. (2020). Our robots, our team: Robot anthropomorphism moderates group effects in human–robot teams. *Frontiers in Psychology, 11*.
Grewal, D., Guha, A., Satornino, C. B., & Schweiger, E. B. (2021). Artificial intelligence: The light and the darkness. *Journal of Business Research, 136*, 229–236.
Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in human behavior, 97*, 304–316.
Grant, A. M., Berg, J. M., & Cable, D. M. (2014). Job titles as identity badges: How self-reflective titles can reduce emotional exhaustion. *Academy of Management Journal, 57*(4), 1201–1225.
Granulo, A., Fuchs, C., & Puntoni, S. (2021). Preference for human (vs. robotic) labor is stronger in symbolic consumption contexts. *Journal of Consumer Psychology, 31*(1), 72–80.
Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York, NY: Guilford publications.
Hertz, N., & Wiese, E. (2019). Good advice is beyond all price, but what if it comes from a machine? *Journal of Experimental Psychology: Applied, 25*(3), 386–395.
Ho, C.-C., & MacDorman, K. F. (2010). Revisiting the uncanny valley theory: Developing and validating an alternative to the Godspeed indices. *Computers in human behavior, 26*(6), 1508–1518.
Höddinghaus, M., Sondern, D., & Hertel, G. (2021). The automation of leadership functions: Would people trust decision algorithms? *Computers in human behavior. Advanced online publication, 116*, 1–14.
Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science, 49*(1), 30–50.
Hyun, S. S. (2010). Predictors of relationship quality and loyalty in the chain restaurant industry. *Cornell Hospitality Quarterly, 51*(2), 251–267.
IBM. (2017). *How chatbots can help reduce customer service costs by 30%*. https://www.ibm.com/blogs/watson/2017/10/how-chatbots-reduce-customer-service-costs-by-30-percent/. Accessed April 5, 2021.
Insider. (2021). *Chatbot market in 2021: Stats, trends, and companies in the growing AI chatbot industry*. Feb 8, 2021. https://www.businessinsider.com/chatbot-market-stats-trends. Accessed April 5, 2021.
Jayanti, R. K., & Whipple, T. W. (2008). Like me… like me not: The role of physician likability on service evaluations. *Journal of Marketing Theory and Practice, 16*(1), 79–86.
Johnston, K. (2019). Feeling emotional? The machines know. *The Boston Globe*.
Jurczyk, L. (2018). Rule the speed of your chats with the new conversation delay. *ChatBot 2 MIN READ*. Mar 7, 2018. https://www.chatbot.com/blog/manage-the-speed-of-the-chat-with-the-conversation-delay/. Accessed April 5, 2021.
Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Macmillan.
Kilens, M. (2020). *2020 State of Conversational Marketing*. DRIFT. https://www.drift.com/blog/state-of-conversational-marketing/?utm_source=salesforce&utm_medium=blog. Accessed April 5, 2021.
Kristof-Brown, A. L., Zimmerman, R. D., & Johnson, E. C. (2005). Consequences of Individuals's Fit at Work: A Meta-Analysis of Person-Job, Person-Organization, Person-Group, and Person-Supervisor Fit. *Personnel Psychology, 58*(2), 281–342.
Evans, S. C., Roberts, M. C., Keeley, J. W., Blossom, J. B., Amaro, C. M., Garcia, A. M., … Reed, G. M. (2015). Vignette methodologies for studying clinicians' decision-making: Validity, utility, and application in ICD-11 field studies. *International journal of clinical and health psychology, 15*(2), 160–170.
Kurzweil, R. (2005). *The singularity is near: When humans transcend biology*. New York, NY: Penguin.
Lamkin, J., Maples-Keller, J. L., & Miller, J. D. (2018). How likable are personality disorder and general personality traits to those who possess them? *Journal of personality, 86*(2), 173–185.
Lim, K. H., Benbasat, I., & Ward, L. M. (2000). The role of multimedia in changing first impression bias. *Information Systems Research, 11*(2), 115–136.
Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. *Journal of business research, 129*, 911–926.
Lv, X., Liu, Y., Luo, J., Liu, Y., & Li, C. (2021). Does a cute artificial intelligence assistant soften the blow? The impact of cuteness on customer tolerance of assistant service failure. *Annals of tourism research, 87*, 1–19.
Lynch, J. G., Jr (1982). On the external validity of experiments in consumer research. *Journal of Consumer Research, 9*(3), 225–239.
MacKenzie, S. B., & Lutz, R. J. (1989). An empirical examination of the structural antecedents of attitude toward the ad in an advertising pretesting context. *Journal of Marketing, 53*(2), 48–65.
Martinez, A. D., Laird, M. D., Martin, J. A., & Ferris, G. R. (2008). Job title inflation. *Human resource management review, 18*(1), 19–27.
McLeay, F., Osburg, V. S., Yoganathan, V., & Patterson, A. (2021). Replaced by a Robot: Service Implications in the Age of the Machine. *Journal of Service Research, 24*(1), 104–121.
Mullinix, K. J., Leeper, T. J., Druckman, J. N., & Freese, J. (2015). The generalizability of survey experiments. *Journal of Experimental Political Science, 2*(2), 109–138.
Murphy, R. R. (2019). *Introduction to AI robotics*. Cambridge, MA: MIT press.
Nass, C., & Lee, K. M. (2001). Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction. *Journal of experimental psychology: applied, 7*(3), 171–181.
Nass, C., Steuer, J., & Tauber, E. R. (1994). *Computers are social actors*. Paper presented at the Proceedings of the SIGCHI conference on Human factors in computing systems, Boston.
Neary, S. (2014). Professional identity: What I call myself defines who I am. *Carrer Matters, 2*(3), 14–15.
Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *Journal of Advertising, 19*(3), 39–52.
OPUS. (2018). *OPUS Group Interim Report*. https://opus.global/media/44137/opus-q3-2018-report-eng.pdf. Accessed April 5, 2021.
Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services, 55*, 1–9.
Pronin, E. (2008). How we see ourselves and how we see others. *Science, 320*(5880), 1177–1180.
Press, G. (2019). *AI Stats News: 86% Of Consumers Prefer Humans To Chatbots*. Oct 2, 2019. https://www.forbes.com/sites/gilpress/2019/10/02/ai-stats-news-86-of-consumers-prefer-to-interact-with-a-human-agent-rather-than-a-chatbot/?sh=6c5c66722d3b. Accessed April 5, 2021.
Pulles, N. J., & Hartman, P. (2017). Likeability and its effect on outcomes of interpersonal interaction. *Industrial Marketing Management, 66*, 56–63.
Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research, 116*, 68–74.
Reinhard, M. A., & Messner, M. (2009). The effects of source likeability and need for cognition on advertising effectiveness under explicit persuasion. *Journal of Consumer Behaviour: An International Research Review, 8*(4), 179–191.
Sahota, N. (2020). Worried About AI Taking Your Job? More Likely, It Will Become Your Boss. *Forbes,* Oct 26, 2020, https://www.forbes.com/sites/neilsahota/2020/10/26/worried-about-ai-taking-your-job-more-likely-it-will-become-your-boss/?sh=61fd53321559. Accessed April 5, 2021.
Salem, S. F., & Alanadoly, A. B. (2020). Personality traits and social media as drivers of word-of-mouth towards sustainable fashion. *Journal of Fashion Marketing and Management: An International Journal., 24*(1), 24–44s.
Salvaggio, A. N., Schneider, B., Nishii, L. H., Mayer, D. M., Ramesh, A., & Lyon, J. S. (2007). Manager personality, manager service quality orientation, and service climate: Test of a model. *Journal of Applied Psychology, 92*(6), 1741–1750.
Sandoval, E. B., Brandstatter, J., Yalcin, U., & Bartneck, C. (2020). Robot Likeability and Reciprocity in Human Robot Interaction: Using Ultimatum Game to determinate Reciprocal Likeable Robot Strategies. *International Journal of Social Robotics*, 1–12.
Shellenbarger, S. (2014). Why Likability Matters More at Work. *The Wall Street Journal*. https://www.wsj.com/articles/why-likability-matters-more-at-work-1395788402. Accessed April 5, 2021.
Sinclair, R. C., Moore, S. E., Mark, M. M., Soldat, A. S., & Lavis, C. A. (2010). Incidental moods, source likeability, and persuasion: Liking motivates message elaboration in happy people. *Cognition and emotion, 24*(6), 940–961.
Steain, A., Stanton, C. J., & Stevens, C. J. (2019). The black sheep effect: The case of the deviant ingroup robot. *PloS one, 14*(10), Article e0222975.
Tan, X. Z., Reig, S., Carter, E. J., & Steinfeld, A. (2019). From one to another: how robot-robot interaction affects users' perceptions following a transition between robots. *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 114–122.
Tenney, E. R., Turkheimer, E., & Oltmanns, T. F. (2009). Being liked is more than having a good personality: The role of matching. *Journal of Research in personality, 43*(4), 579–585.
Trautt, G. M., & Bloom, L. J. (1982). Therapeugenic factors in psychotherapy: The effects of fee and title on credibility and attraction. *Journal of Clinical Psychology, 38*(2), 274–279.

Userlike. (2020). *What Do Your Customers Actually Think About Chatbots?*, June 26, 20201, https://www.userlike.com/en/blog/consumer-chatbot-perceptions. Accessed April 5, 2021.
Venkatesh, V., & Goyal, S. (2010). Expectation disconfirmation and technology adoption: Polynomial modeling and response surface analysis. *MIS Quarterly, 34*(2), 281–303.
Vlačić, B., Corbo, L., e Silva, S. C., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research, 128*, 187–203.
Walther, J. B., Loh, T., & Granka, L. (2005). Let me count the ways: The interchange of verbal and nonverbal cues in computer-mediated and face-to-face affinity. *Journal of language and social psychology, 24*(1), 36–65.
Wesche, J. S., & Sonderegger, A. (2019). When computers take the lead: The automation of leadership. *Computers in Human Behavior, 101*, 197–209.
Woolway, T., & Harwood, C. (2015). Do titles matter in sport psychology? Performer attitudes toward professional titles and the effect of a brief intervention. *The Sport Psychologist, 29*(2), 171–182.
Xiao, L., & Kumar, V. (2019). Robotics for customer service: A useful complement or an ultimate substitute? *Journal of Service Research, 24*(1), 9–29.
Yoo, J. J., Arnold, T. J., & Frankwick, G. L. (2012). Effects of positive customer-to-customer service interaction. *Journal of Business Research, 65*(9), 1313–1320.
Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking, 21*(8), 491–497.

Further reading

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*(9), 389–399.
Krukowski, K. (2017). The Effects of Employee Job Titles on Respect Granted by Customers. *Paper presented at the Seventh International Engaged Management Scholarship Conference*.
Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650.
Melling, L. (2019). What's in a name? Job title and working identity in professional services staff in higher education. *Perspectives: Policy and Practice in Higher Education, 23*(5), 48–53.
Van Doorn, J. (2008). Is there a halo effect in satisfaction formation in business-to-business services? *Journal of Service Research, 11*(2), 124–141.

Yongwoog "Andy" Jeon (Ph.D., University of Texas at Austin) is Assistant Professor of Marketing in the Department of Marketing, College of Business at Northern Illinois University. He studies how individuals psychologically and behaviorally respond to marketing messages delivered via interactive technologies such as artificial intelligence (AI), skippable YouTube video ads or immersive VR (e.g., metaverse).