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Leveraging "*human-likeness*" of robotic service at restaurants

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ABSTRACT

Despite the rise of human-robot interaction research, the mixed findings of human-likeness in consumer evaluation exist. Focusing on the restaurant sector, this research investigates how service robots' varying levels of human-likeness of attributes (i.e., *visual, vocal* and *verbal*) influence consumption outcomes (e.g., service encounter evaluation, revisit intentions and positive word of mouth intentions) and the underlying mechanisms through cognition (i.e., perceived credibility) and positive emotion per *Appraisal Theory*. Drawing on a consumer experiment involving a total of 587 participants, results suggest that humanlike *voice* emerges as a dominant attribute affecting all three consumption outcomes. Humanlike *language style* positively affects service encounter evaluation but barely affects the other two outcomes. The significant effect of humanlike *voice* on three consumption outcomes is only explained by positive emotion whereas the effect of humanlike *language style* on service encounter evaluation is explained by both cognition (i.e., perceived credibility) and emotion.

1. Introduction

Service robot is defined as the "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers." (Wirtz et al., 2018, p. 909). Research estimates that the service robot market is growing rapidly from USD 37.0 billion in 2020 to a projected value of USD 102.5 billion by the end of 2025, with a compound annual growth rate of 22.6% (Markets and Markets., 2020). For example, the restaurant industry is looking intensely at the application of service robots due to external pressures such as increasing wages, shrinking labor supply and flatten productivity, as well as internal forces including cost efficiencies, staffing flexibility and safety concerns (Pouliot, 2016). "Penny", a robot food runner, has shown to increase server's time by an average 40% in dining facilities across US and international markets (Luna, 2020). Moreover, the recent coronavirus (COVID-19) pandemic has made such application unprecedentedly relevant to the hospitality industry as we are looking at a probable near future with more robotic application to decrease human touch (Matthews, 2020).

Meanwhile, customers' positive service evaluation and consumption outcomes drive the employment of service robots at the frontline (Murphy et al., 2019). Studies have shed light on a range of factors affecting service robot integration in hospitality experiences (Lin et al., 2019; Lu et al., 2019; Qiu et al., 2019). Among the factors, anthropomorphism, which is the assignment of a human form, characteristics, or behavior to nonhuman objects, emerges as a decisive force (Bartneck et al., 2009). In other words, service robots can be designed with some degree of resemblance of human in height, shape, and/or body parts.

However, customers engaged in human-robot interaction (HRI) in service settings are found to have mixed attitudes toward anthropomorphic robots. Some indicate positive experiences or stronger adoption intention when human-likeness is greatly perceived (Lin et al., 2019; Qiu et al., 2019; van Pinxteren et al., 2019). For instance, van Pinxteren et al. (2019) found that anthropomorphism of a greeter robot increases perceived enjoyment and adoption intention via trust. While the stream of the findings may be true, other studies reveal that negative attitudes such as eeriness, scariness, or perceived threat to human identity, can be evoked when anthropomorphism reaches a high level (Mende et al., 2019; Yu, 2019). Therefore, the link between service robot anthropomorphism and customers' service evaluation remains unclear.

Due to the dynamic and unstructured nature of service encounters, humanlike capabilities of anthropomorphic robots such as voice, visual, or haptic features are simultaneously crucial in shaping interaction experience (Belk, 2016). So far, visual features have received

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predominant attention (e.g., Phillips et al., 2018). Nonetheless, service encounters involve multi-sensory communications (Lee et al., 2019). The encounters between human and service robots should also be examined through an integrative mechanism comprising multiple key anthropomorphic features (Fink, 2012). Thus, there is a need to examine the relationship between anthropomorphism and customers' service evaluation through a multi-dimensional view of human-likeness.

Echoing the essence of appraisal theory (Lazarus, 1991), customers' evaluation of anthropomorphic features is the result of the cognitive-affective process provoked by the human-likeness of service robots. In the context of service robots, the cognitive and emotional mechanisms include customers' beliefs of the robot's ability to accomplish tasks successfully as well as their affection stimulated through the interaction (Kim et al., 2019; Lin et al., 2019). Customers perceive artificial intelligence to be more reliable than its human counterpart, particularly when built in with humanlike features (Graefe, 2016). Anthropomorphic design also helps generate users' emotional responses and rapport building (Qiu et al., 2019). However, extremely scarce literature in hospitality and tourism has examined such mechanism between the human-likeness of service robots and customers' evaluation.

In this study, we adopt restaurant as the research context considering the increasing applications of service robots in this business sector (Gilbody-Dickerson, 2019). The current study holds significance in three ways. First, it identifies the nature of the relationships between key anthropomorphic attributes of robotic servers and customers' service evaluation in the restaurant setting. Second, this study investigates guests' responses to anthropomorphic attributes of robotic servers through a multi-dimensional evaluation approach. Finally, it scrutinizes such relationships by incorporating principal concepts from appraisal theory to further explain the identified relationships. In accordance, the objectives of this research are to *investigate **1)** how* service robots' multi-dimensional humanlike features (i.e., *visual, vocal* and *verbal*), when evaluated concurrently, influence consumers' evaluation of the service encounter and their behavioral intentions; and ***2)*** the underlying mechanisms through perceived credibility and emotion to explain customers' responses to robotic service interactions.

2. Literature review

2.1. The growing application of service robots in restaurants

Service robots have been broadly adopted in various consumption domains including home appliances (e.g., autonomous vacuum cleaner), retail stores (e.g., robot shop assistant), automobiles (e.g., self-driving cars), as well as tourism and hospitality (Nestlé, 2014). In recent years, embracement of service robots in hospitality and tourism has received increasing attention (e.g., Choi et al., 2020, 2019; Tussyadiah, 2020; Yu, 2019). Due to the topic's nascent nature, the exploration started with conceptual analyses focusing on the adoption of service robots (e.g., Ivanov et al., 2017), as well as opportunities and challenges faced by academics and the industry (e.g., Tung and Law, 2017). Since then, some contributions have been made to reflect the perceived differences between human staff versus service robots (e.g., Ho et al., 2020). Moreover, hospitality customers' adoption intention and their evaluation of HRI have become a focal point of research (Lin et al., 2019; Lu et al., 2019; Qiu et al., 2019; Prentice et al., 2020).

Regardless of the mixed findings and the subtle perspective differences, researchers have reached the consensus that service robot anthropomorphism plays an essential role in constructing hospitality customers' HRI experiences (Choi et al., 2019; Murphy et al., 2019; Qiu et al., 2019; Tussyadiah and Park, 2018). The restaurant industry is one of the frontline sectors grasping the growing trend of service robots. Uses of service robots include but not limited to making food, greeting customers, taking food orders, and/or delivering meals (Gilbody-Dickerson, 2019). We adopt restaurant as the research context for this study because of the increased applications of service robots in restaurant industry, which makes it a representative applied setting amongst various hospitality and tourism sectors. Research indicates that by adopting robotic service and artificial intelligence, restaurants will benefit from reduced labor cost, increased sales, enhanced employee skills, and improved service quality and efficiency (Berezina et al., 2019; Ivanov and Webster, 2017). If done properly, HRI can also enhance customers' overall dining experience and loyalty (Qiu et al., 2019).

2.2. Anthropomorphism and service encounter

The relationship between anthropomorphism and user acceptance has been extensively explored in the HRI literature (Duffy, 2003; Złotowski et al., 2015). Anthropomorphism describes people's propensity to ascribe human characteristics to non-lifelike objects (Fink, 2012). Previous research has demonstrated that robots with humanlike features are more likely to provoke people's social responses, which in turn lead to greater acceptance (Duffy, 2003; Eyssel and Kuchenbrandt, 2011). Theoretically, Epley, Waytz, and Cacioppo (2007) indicate that familiarity is the key when interpreting anthropomorphism, as people tend to attribute qualities which they are familiar with to non-human artifacts to make them more informed, understandable, or predictable. This is similar to the argument that people are unconsciously applying stereotypes and heuristics when respond to the humanlike design cues of an object (Fink, 2012).

While the positive link between anthropomorphism and user evaluation and adoption intention has been well documented in HRI (e.g., Eyssel et al., 2012), service automation (e.g., van Pinxteren et al., 2019), and hospitality and tourism (e.g., Qiu et al., 2019), opposite findings show negative responses exist under certain conditions for various reasons (e.g., Ferrari et al., 2016; Mende et al., 2019). The uncanny valley theory is a prevailingly adopted account for such negative responses (Mori, 1970). The theory posits that people's reaction to anthropomorphic robots would shift from acceptance to rejection as human-likeness approaches a high level (Mori, 1970). Drawing on the research of intergroup distinctiveness in social psychology, Ferrari and colleagues (2016) found that concerns for potential damage to humans and their identity may elevate if the robots resemble human physical appearances too much, blurring identity boundaries and impairing human distinctiveness.

Service encounter refers to the interaction between a customer and a service provider (Surprenant and Solomon, 1987), as well as other service elements such as environment and process (Walker, 1995). Service encounter is fundamentally evolving in today's reality because the interface is becoming increasingly technology-driven instead of human-driven (Larivière et al., 2017). Robot is one of the most recent and major technologies in service encounter. Customers tend to embrace service robots at a more comfortable rate with designs mimicking appropriate levels of human qualities (van Pinxteren et al., 2019). Based on the ascending degree of human-likeness in *physical appearance*, service robots could be classified as mechanoid, humanoid and android (Dautenhahn and Ghauoi, 2014; Walters et al., 2008a). Mechanoids are machine-like in *physical appearance* without obvious humanlike features; humanoids possess some humanlike features that are stylized, simplified or made like cartoon characters; androids are as close to human beings as technology can achieve with the purpose to be perceived as fully human (Walters et al., 2008a). In this study, humanlike *appearance* is confined to *physical looks* of the service robot to eliminate alternative interpretations of appearance. Our study design on the robotic server's *physical appearance* follows this classification, of which the three types are also evidenced in service setting.

2.3. Humanlike attributes and service evaluations

Besides the anthropomorphic levels, researchers also identified different forms of human-likeness built in service robots. As one of the most overt and distinctive attributes, a robot's physical shape (e.g., eyes, faces, hands) is found to have a strong influence on users' interaction dynamics with robots (Fink, 2012; Phillips et al., 2018). When comparing humanoid to mechanoid robots in terms of physical appearance, most of the studies agreed that humanoid design is favored over machine-like appearance (Walters et al., 2008a). For example, Zhu and Chang (2020) found that compared to mechanoid robots, robotic chef with humanoid hands leads to positive food quality prediction. Humanoids are generally perceived as more intelligent and competent than mechanoids. Goudey and Bonnin (2016) found that consumers express greater acceptance of a companion robot with partially anthropomorphic appearance than complete machinelike appearance. Research also shows that by building a moderate level of human appearance in a robot's look, perceived similarity (Epley et al., 2007), trust (Mathur and Reichling, 2009), predictability (Eyssel and Kuchenbrandt, 2011), or perceived intelligence (Bartneck et al., 2009) may be triggered, leading to positive attitudes towards HRI.

However, per research conducted in related fields, when human appearance reaches its extreme end (i.e., android), users tend to avoid interaction. Ferrari et al. (2016)'s study showed that androids receive the highest concerns for potential threat to human identities, followed by humanoids and then mechanoids. Pictures of intermediate prosthetic robot hands were perceived more eerie compared to those of either mechanical or human hands (Poliakoff et al., 2013). Others attributed the negative evaluation to people's difficulty in object categorization (Yamada et al., 2013). When the physical appearance of a nonhuman agent approaches an absolute end, users will find it highly difficult to categorize the agent as human or nonhuman, thus triggering cognitive load and negativity (Yamada et al., 2013). Based on the discussion, we propose the following hypothesis.

H1. Medium levels of *humanlike physical appearance* lead to greater positive responses for restaurant services, including a) service encounter evaluation, b) revisit intentions, and c) word of mouth, compared to low and high levels of humanlike *physical appearance*.

Voice is an important dimension in service encounter communications (Burgers et al., 2000). For example, employee vocal attractiveness is found to significantly influence customers' expectation and service encounter satisfaction (Bartsch, 2008). Likewise, vocal cues are a crucial humanlike attribute in HRI. Research shows that people tend to attribute heuristics that are normally applied to human to computer interfaces with voice outputs (Nass and Brave, 2005). A robot with synthesized mechanical voice lead to significantly further approach distances than with humanlike voices (Walters et al., 2008b). Eyssel et al. (2012) found that participants are more like to anthropomorphize a robot psychologically when humanlike voice is employed. And perceived anthropomorphism leads to greater positive responses of HRI in hospitality and tourism (e.g., Qiu et al., 2019; Tussyadiah and Park, 2018). Similarly, humanlike sound appears to be more acceptable by participants and elicits positive perceptions compared to robotic sound when interacting with a receptionist robot (Trovato et al., 2015). Therefore, the following hypothesis is proposed.

H2. High (vs. low) levels of *humanlike voice* lead to greater positive responses for restaurant services, including a) service encounter evaluation, b) revisit intentions, and c) word of mouth.

Besides *physical appearance* and voice, people also rely on language style cues to form a mental model of the robot's behavior (Lee et al., 2005). Bischoff and Graefe (1999) noted that combining natural human language with other humanlike features make the robot seem more intelligent and easier to communicate with. Humans in general are capable of using social cues and adapting language style and demeanor to social surroundings. Likewise, language style cues of social relationships in human interactions can also be applied to anthropomorphic design of robots. For example, a robot is perceived more friendly when it addresses people by his/her name compared to when it does not (Kim et al., 2011). A robot with a playful language style leads to more compliance if the request is entertainment-related (Goetz et al., 2003). In the case of hotels' robotic concierge, when robots are anthropomorphized, the effectiveness of their language styles (literal vs. figurative) on customers' service evaluation requires robots to meet the expectancy of human communication norms. For example, research suggests that using a literal and straightforward language style (i.e., literal language) is perceived more appropriate and credible in conversation norms during service interactions, as opposed to an emotional intense language style with exaggeration and metaphors (i.e., figurative language) (Choi et al., 2019; Jensen et al., 2013). Customers tend to exhibit same language preferences when responding to human hotel staffs as to anthropomorphic robots (Ho et al., 2019). In this study, levels of human-likeness in language style refer to the extent to which the robotic server resembles a human service staff by adopting a literal (vs. figurative) language style. Taking the above evidence together, we propose the following hypothesis.

H3. High (vs. low) levels of *humanlike language style* lead to greater positive responses for restaurant services, including a) service encounter evaluation, b) revisit intentions, and c) word of mouth.

2.4. Appraisal theory, perceived credibility, and emotion

Appraisal theory claims that both cognitions and emotions are elicited by appraisals of events (Lazarus, 1991). For instance, one customer may feel unhappy if his/her server is not professional because he/she evaluates that the service received is not worth the money/time spent. Appraisal theory represents an evaluative process starting with an initial evaluation followed by further cognitive and emotional assessments of a relevant stimulus (Lazarus, 1991; Smith and Lazarus, 1993). Appraisal theory can capture the dynamic interactions between an individual and the environmental stimuli in explaining individuals' subsequent behavior (Hosany, 2012; Roseman, 2001). In the current context, consumers are likely to engage in both cognitive and emotional appraisals of the service robots prior to indicating a response. Hence, cognition (i.e., perceived credibility) and emotion are introduced to explain the effect of human-likeness on consumption outcomes.

Previous literature reveals that perceived credibility serves as one of the main explanations for the effect of robot anthropomorphism on customers' positive evaluation (Choi et al., 2019; Mathur and Reichling, 2009; van Pinxteren et al., 2019). Perceived credibility is conceptualized as both trustworthiness and competence (Ayeh, Au, & Law, 2013). Wirtz et al. (2018) indicate that "consumer acceptance of service robots depends on how well robots can deliver on the functional needs and the social-emotional and relational needs to achieve role congruency" (p. 915). Customers are more likely to adopt humanoid service robots because human-like features built in robots promotes trust towards robots (van Pinxteren et al., 2019).

Meanwhile, a robot's humanlike embodiment is found to affect its perceived intelligence (Tussyadiah, 2020). Anthropomorphizing a non-intelligent object is a useful approach to improve reliability as human-likeness is often associated with intelligence and competence in task performance (Wan and Aggarwal, 2015). Therefore, a robot that looks smart and competent will increase customers' confidence about trustworthy services. This further justifies the critical role of perceived credibility, which is chosen as one of the major constructs in the current study. Furthermore, emotion plays a pivotal role for users of social robots in HRI (Fong et al., 2003). Following appraisal theory such interaction can provoke human emotional experience, influencing perceived service quality and satisfaction (Zhang et al., 2008). Therefore, some research efforts have been concentrated on developing robots capable of affective expressions (e.g., Gockley et al., 2006). Likewise, van Pinxteren and colleagues found that anthropomorphism of a humanoid greeter robot positively influences customers' perceived enjoyment and adoption intentions (van Pinxteren et al., 2019). Thus, we propose the following hypotheses.

H4. The effect of *humanlike physical appearance* on consumption outcomes is mediated by a) perceived credibility of the robotic server and b) positive emotion.

H5. The effect of *humanlike voice* on consumption outcomes is mediated by a) perceived credibility of the robotic server and b) positive emotion.

H6. The effect of *humanlike language style* on consumption outcomes is mediated by a) perceived credibility of the robotic server and b) positive emotion.

3. Methods

3.1. Study design

In this study, we explored how varying levels of human-likeness of robotic server's attributes during service interaction can influence customers' service encounter evaluation, revisit intentions, and WOM intentions. We conducted a 3 (appearance human-likeness: low vs. medium vs. high) × 2 (voice human-likeness: low vs. high) × 2 (language style human-likeness: low vs. high) between-subjects experiment using the experimental vignette methodology. Participants were instructed to take part in an online experiment that simulated a dining event and had interactions with a robotic server. Using scenarios, pictorial stimuli, audio stimuli, and textual stimuli, the experimental vignette methodology allows participants to simulate a field event realistically and precisely (Seiter and Weger, 2020). In the hospitality literature, it is a common practice to measure consumers' post-consumption outcomes upon exposure to experimental stimuli (Choi et al., 2019; Seiter and Weger, 2020). In this study, participants were subject to experimental treatments to simulate the service event. At the end of the experiment, they were asked indicated the service encounter evaluation, revisit intentions, and WOM intentions. These three post-consumption outcomes were carefully selected based on their importance to assess positive or negative service experiences agreed in existing literature (e.g., Choi et al., 2019; Hutchinson et al., 2009; Ryu and Jang, 2007).

We selected a casual dining restaurant as the research setting of this study for a couple of considerations. First, casual-dining restaurants capture a wide consumer population and dining events while equally supporting utilitarian and hedonic consumption goals. Second, technology-enabled services (e.g., kiosk and mobile ordering) have already become a norm as service tools in quick-service restaurants (QSR) and human interaction play a less important role than other segments. In upscale restaurants, robots are less likely replace human staff in service interactions due to the sophistication required for human interactions.

3.2. Stimuli and procedure

The experiment was comprised of scenarios, pictorial, audio, and textual stimuli to characterize the situation experienced by the participants (e.g., a service robot serving the table).

The scenario envisaged both human staff and the robotic server were working at the restaurant assuming different roles. Participants were first greeted by a human host and then served by a robotic server. We chose a human-robot co-existing workplace because of a general preference for human-robot hybrid services indicated by previous research (Singer, 2016).

Levels of humanlike appearance were manipulated through pictorial stimuli (i.e., pictures of service robots). In the low humanlike appearance treatment, the robot was designed to carry food without any humanlike design. With medium levels of human-likeness, the robot presented basic body features (e.g., head, arms, and legs) but did not exhibit any advanced and nuanced features such as facial expression. In the high humanlike appearance treatment, the robot presented extreme humanlike facial structures (i.e., see the "Sophia" robot as a synthetic human) and almost looked like a real human. To manipulate the human-likeness in language style, two versions of conversation scripts between the "customer" and the "robotic server" were created. In the high humanlike language style treatment, the robotic server's language was plain and straightforward (i.e., literal language) (e.g., "Good choice. It is a strong drink. I will get it for you now"). In the low humanlike language style treatment, the robotic server's language was vivid and affectively intense (i.e., figurative language) (e.g., "Wooooo, that stuff will definitely get you hyper! I can never handle more than two!"). We recruited two research assistants to roleplay both sets of conversations and audio recorded. For a clear distinction between the high versus low levels of humanlike voice, we used the original recordings to characterize high humanlike voice. For the low humanlike voice treatment, we requested a professional audio technician to modify the voice pitch, speed, and tempo of the "robotic server" to generate a monotonous speech style, which characterizes a robotic voice (Sugiura et al., 2015). The "customer's" voice was held identical between two voice treatments.

3.3. Sample and measures

Consumer participants were recruited from Amazon Mechanical Turk (www.mturk.com). The appropriateness of using MTurk consumers for experimental studies has been validated in previous research, especially given participants' attentiveness to experimental instructions (see Buhrmester et al., 2011). Several screening criteria were used to recruit participants: 1) age above 18-year-old, 2) currently residing in the United States, and 3) have visited a quick-service, casual dining, and fine dining restaurant in the past 12 months to ensure participants' representation of all segments. Participants who failed to meet any of the above criteria were blocked from this study. Service encounter evaluation was measured using an existing three-item scale (Choi et al., 2019, Cronbach's alpha = 0.928). Revisit intentions were measured with three items such as "I am willing to visit this restaurant again" (Cronbach's alpha = 0.904). WOM intentions was measured with three items such as "I will say positive things about this restaurant to other people" (Hutchinson et al., 2009, Cronbach's alpha = 0.907). Perceived credibility of the robotic server was measured with five-item semantic scale such as "insincere/sincere" (Ayeh et al., 2013; Choi et al., 2019, Cronbach's alpha = 0.887). Emotion was measured using an existing scale with four-item semantic scale such as "unhappy/happy," "bored/entertained," (Ryu and Jang, 2007, Cronbach's alpha = 0.902). We converted all measurement items in a composite score for data analysis in the subsequent sections.

4. Results

4.1. Three-way ANCOVA and process model

The final data contained 587 valid responses amongst which 41.4% were females, 44.4% were in the age bracket of 26–34 years, followed by 35.4% were in the age bracket of 35–54. Most of the participants (64.3%) were Caucasian/White, and 51.3% held a bachelor's degree. For manipulation checks, participants who were subjected to high levels of humanlike *physical appearance* stimulus (e.g., android) reported significantly greater values of levels of humanlike-ness in the robot's appearance than those exposed to medium and followed by low levels of human *physical appearance* stimuli ($M_{\text{High-appearance}} = 4.66$; $M_{\text{Medium-appearance}} = 3.67$; $M_{\text{Low-appearance}} = 3.02$; $F = 36.97$, $p < .001$). Participants assigned to high (vs. low) levels of humanlike *voice* reported significantly greater levels of human-likeness in *voice* ($M_{\text{High-voice}} = 5.25$, $M_{\text{Low-voice}} = 3.49$, $t = 12.18$, $p < .001$). Participants assigned to the high (vs. low) levels of humanlike *language style* condition also reported significantly larger (vs. smaller) values of human-likeness of the *language style* (M $_{\text{high-language}}$ = 5.32; M $_{\text{low-language}}$ = 4.97, $t = 2.99$, $p < .01$). Participants also indicated that the situation described in the scenario was easy for them to understand (M = 5.72), was easy to imagine themselves in the situation (M = 5.54), and easy to imagine the scenario happen in real life (M = 5.57). Thus, both realism checks and manipulation checks were deemed successful.

A three-way ANCOVA analysis was conducted individually for service encounter evaluation, re-visit intentions, and WOM intentions (see Table 1). Respondents' gender, age, and income were entered as control variables. As for humanlike a*ppearance*, post-contrast analysis indicated that medium levels of humanlike *physical appearance* (e.g., humanoids) were viewed similarly to the other two levels ($p = .06$). Medium levels of humanlike *physical appearance* (e.g., humanoids) were less favored than the other two *physical appearance* stimuli in terms of revisit intentions ($p < .05$). Thus, diners were more likely to visit the restaurant again when the robotic servicer exhibited low levels (e.g., mechanoid) and high levels of humanlike *physical appearance* (e.g., android) than medium levels (e.g., humanoid). Hypotheses $1_{(a,\ b,\ c)}$ and 4 were thus rejected. *Voice* ($F_{(1,\ 570)} = 7.098$, $p < .01$) and *language* style ($F_{(1,\ 570)} = 6.609$, $p < .01$) exhibited a significant main effect on service encounter evaluation. Participants indicated higher positive encounter evaluation when the service robot exhibited high levels of humanlike *voice* (vs. low levels) and high levels (vs. low levels) of humanlike *language*. For revisit intentions, humanlike *voice* had a significant positive effect ($F_{(1,\ 570)} = 4.352$, $p < .05$). High levels of humanlike *voice* had a positive effect on re-visit intentions compared to low levels of humanlike *voice* ($p < .05$). For WOM intentions, the results revealed a positive effect of humanlike *voice* ($F_{(1,\ 570)} = 10.08$, $p < .05$) and an interaction effect between *voice* and *physical appearance* ($F_{(2,\ 570)} = 13.874$, $p < .05$). Like the effect on the other two outcome variables, high (vs. low) levels of humanlike *voice* led to greater positive WOM intentions. Interestingly, the positive effect of a humanlike *voice* was conditioned by the robotic server's *physical appearance*. When the robotic server exhibited low-to-medium levels of humanlike *physical appearance*, high (vs. low) levels of humanlike *voice* led to greater WOM intentions. In the case of high levels of human *physical appearance,* the results flipped so that low (vs. high) levels of humanlike *voice* lead to greater positive WOM intentions. Thus, findings have fully supported *Hypothesis* $2_{(a,\ b,\ c)}$ and *Hypothesis* 3_a. Figs. 1–3 illustrate the three-way ANCOVA results.

4.2. Mediating effect of cognition and emotion

The mediating effects of perceived credibility and emotion were analyzed through Hayes (2018) PROCESS macro (Model 4) with recommended bootstrapping technique (resampling 10,000 for bias correction, IBM SPSS version 25). Given the rejection of hypothesis 1 and 4 in relation to humanlike *physical appearance*, we only included *voice* and *language* style in the mediation analyses. According to the Bootstrapping results, the significant effect of *voice* on service encounter evaluation was fully mediated by positive emotion (95% confidence interval CI = .0154, .3959) given absence of a direct effect. Perceived credibility failed to emerge as a significant mediating variable. For the indirect effect of *language style* on service encounter evaluation, the results suggested that both emotion (95% CI = .0186, 0.4010) and perceived credibility (95% CI = .0493, 0.3800) were significant mediating variables.

We performed the same analysis on the indirect effect of *voice* on revisit intentions and WOM intentions, individually. For revisit intentions, only emotion emerged to be a significant mediator accounting for the positive effect of humanlike *voice* (95% CI = .0129, 0.3588). Likewise, emotion also significantly mediated the effect of a humanlike *voice* on WOM intentions (95% CI = .0142, 0.3618). In summary, the significant effect of a humanlike *voice* on three outcome variables was consistently explained by positive emotion. Thus, the results have fully supported *Hypothesis* 5_b while rejecting 5_a. Both emotion and perceived credibility explained the indirect effect of humanlike *language style* on service encounter evaluation, lending support to Hypothesis $6_{(a,\ b)}$.

5. Discussion and conclusion

Given the rising application of service robots and scholars' appeals for examining human-robot interactions in various service contexts (Mende et al., 2019; Wirtz et al., 2018), it becomes pressing for hospitality scholars to take a deep dive into guest responses to robotic services. According to this study, the robot's *voice* is a dominant attribute that drives service encounter evaluation and behavioral intentions (e.g., revisit intentions and WOM intentions). Diners consistently indicated greater positive ratings across three consumption outcomes when the service robot had high levels of humanlike *voice*. Our results echoed previous attempts which suggest that humanlike *voice* increases perceived trustworthiness of the robot and intentions to approach/avoid (Edwards et al., 2019; Qiu and Benbasat, 2009). In Niculescu et al.'s

Table 1
a Three-way ANCOVA analysis.

	Consumption Outcomes											
	Service Encounter Evaluation				Loyalty (Revisit Intentions)				WOM intentions			
Source	Type III Sum of squares	df	F	P	Type III Sum of squares	df	F	P	Type III Sum of squares	df	F	P
Corrected model	47.994a	14	1.814	0.034	35.927a	14	1.225	0.252	37.978a	14	1.421	0.138
Intercept	845.964	1	447.572	0	859.426	1	410.264	0	827.786	1	433.513	0
gender	0.784	1	0.415	0.52	0.186	1	0.089	0.766	0.15	1	0.078	0.78
age	0.197	1	0.104	0.747	3.578	1	1.708	0.192	1.763	1	0.923	0.337
income	0.482	1	0.255	0.614	4.82	1	2.301	0.13	0.047	1	0.025	0.875
Physical appearance	9.027†	2	2.388	0.093	10.551†	2	2.518	0.081	2.419	2	0.634	0.531
Voice	13.416**	1	7.098	0.008	9.118*	1	4.352	0.037	10.08*	1	5.279	0.022
Language	12.492**	1	6.609	0.01	2.008	1	0.958	0.328	4.112	1	2.153	0.143
Physical appearance * Voice	7.95	2	2.103	0.123	1.605	2	0.383	0.682	13.874*	2	3.633	0.027
Physical appearance * Language	2.477	2	0.655	0.52	1.24	2	0.296	0.744	4.683	2	1.226	0.294
VOICE * Language	0.35	1	0.185	0.667	0.819	1	0.391	0.532	0.844	1	0.442	0.507
Physical appearance * Voice * Language	0.85	2	0.225	0.799	2.151	2	0.513	0.599	0.426	2	0.112	0.894
Error	1077.368	570			1191.949	570			1088.405	570		
Total	18819.778	585			15,665	585			16347.333	585		

†p < .1; *p < .05; **p < .01; ***p < .001.

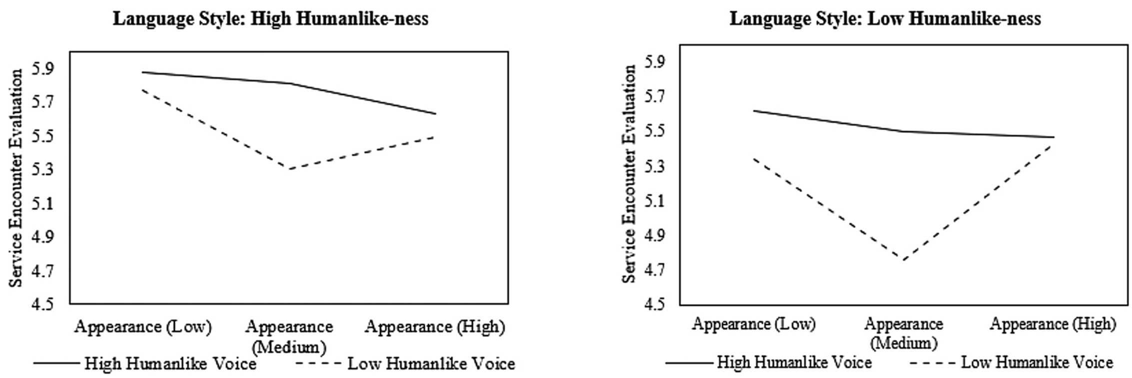

Fig. 1. The effect of three humanlike attributes on service encounter evaluation.

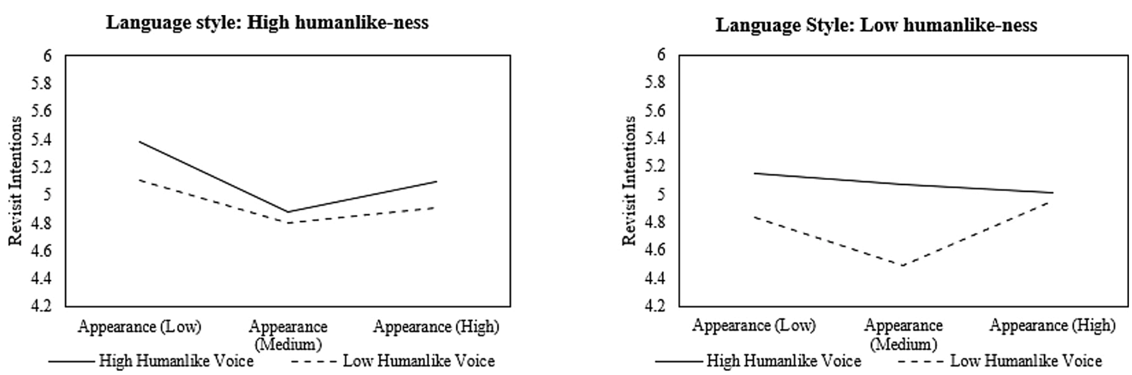

Fig. 2. The effect of three humanlike attributes on revisit intentions.

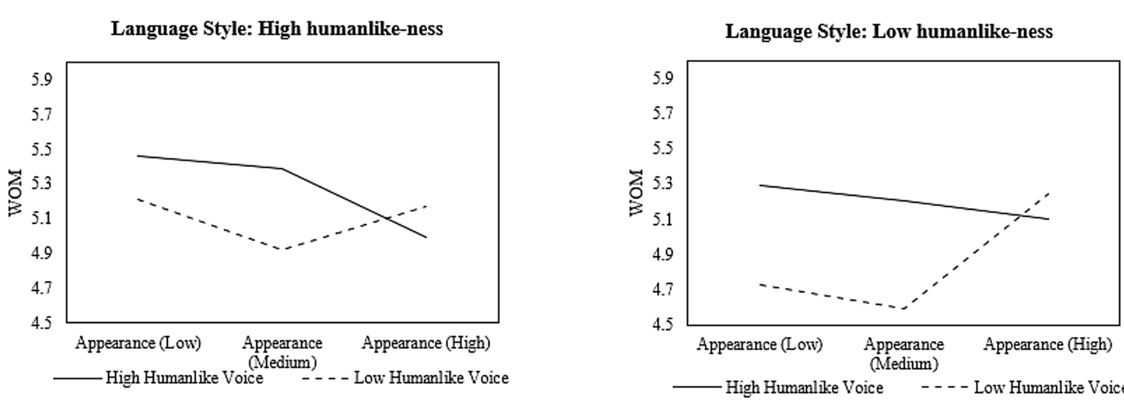

Fig. 3. The effect of three humanlike attributes of service robots on WOM intentions.

(2013) study, the robot's *voice* pitch is found to influence overall interaction quality as well as the robot's attractiveness and perceived enjoyment of the user. Extending such a stream of literature, our study further confirms the positive influence of a robotic server's humanlike *voice* on diners' service encounter evaluation and behavioral intentions toward the restaurant after interacting with the service robot.

The results also suggest a positive effect of humanlike *language style* on service encounter evaluation, which has corroborated the previous finding that conversational norms of human service providers shall be extended to service robots as a representation of human-likeness (Choi et al., 2019; Epley et al., 2007). Previous studies (Choi et al., 2019; Trovato et al., 2015) attribute the preference for humanlike *voice* and *language style* to the notion of anthropomorphism such that consumers apply human communication norms for robots that have human features. In line with this positive view on humanlike-ness in service robots, our findings have evidenced the notion of Mende et al. (2019) that consumers' negative response towards the human-likeness of service robots is context dependent. For example, a dining event at restaurants is conducive to social belongingness which is considered a built-in coping mechanism that alleviates negative feelings associated with identity threat and negative emotions. Restaurant services are hedonism-centric, consumers are less likely to experience negative emotions in the surrounding of other customers and one's own group. Amongst conflicting stances of humanlike-ness in robotic design, our findings have favored a positive outlook of having robotic staff for service interaction. Besides adding evidence to the overall favoritism of service robots' human-likeness in the restaurant setting, our study testifies how the three humanlike-attributes operates differently in driving consumption outcomes.

In our study, levels of humanlike *physical appearance* exhibit minimal influence on consumption outcomes. Although studies found adverse perceptions and negative emotions associated with an extreme human look (e.g., Ferrari et al., 2016; Goudey and Bonnin, 2016), our finding has resonated with recent dialogues that certain settings, which foster social-belongingness such as dining in restaurants, can mitigate the potential negative effect of humanlike look of service robots (Mende et al., 2019). Social belongingness (i.e., feeling connected with others) is a crucial aspect of human adequacy and is theorized to mitigate an identity-related threat such as interacting with a humanlike robot (Shnabel et al., 2013; Mende et al., 2019). Different from previous research examining HRI in an isolated environment, this study instills social belonging considering the presence of other humans in a shared environment which was specified in the scenario. As a result, the previously claimed “uncanny valley” associated with human *appearance* is attenuated. Another possible reason accounting for the marginal effect of humanlike *appearance* could be the increased familiarity of robotic services in service settings. Familiarity is also a key factor that reduces uncertainty and fear for unknowns. Even repeated exposure of an unknown object could enhance consumers’ positive emotion due to heightened familiarity and reduced uncertainty (“stimulus habituation”) (Montoya et al., 2017). The increased exposure of information about robots might have de-sensitized respondents to robots’ human *appearance*. Our results also suggest that interactions with androids and mechanoids seem to have engendered greater re-visit intentions than humanoids. Despite previous controversial views on robots’ humanlike *appearance*, this finding coincides with Prakash and Rogers (2015) that perceptions of robots are rated more positively for mechanical and completely human-like appearance than mixed appearance because of likeability. According to Prakash and Rogers (2015), robots that have partial human appearance could be viewed as a faulty replica of humans whereas a complete human face is considered more *relatable* to a real person particularly in the case when robots perform social tasks traditionally performed by humans.

According to the findings, positive emotion accounts for the underlying mechanism explaining the effect of humanlike *voice* on consumption outcomes. In other words, it is the positive emotion stimulated by high levels of humanlike *voice* that leads to a greater evaluation of the service encounter, revisit intentions, and WOM intentions. Previous search on robotic *voice* also supports the positive effect of a humanlike *voice* which is found to prompt trust, likability, and greater acceptance of the robot (e.g., Edwards et al., 2019; Niculescu et al., 2013; Tamagawa et al., 2011). For example, chatbots are perceived to be more trustworthy and credible with a human *voice* which engenders positive perceptions (Edwards et al., 2019; Qiu and Benbasat, 2009). In a virtual environment, *voice* becomes a dominant source to establish trust and credibility of such interactions. However, in our study there are multiple humanlike cues (e.g., *visual*, *vocal*, and *verbal*) that participate in diners’ evaluation. Because cognitive processing of voice cues could be interfered by verbal stimuli (e.g., humanlike *language*), known as the *verbal overshadowing* effect (e.g., Perfect et al., 2002), *verbal* cues can surpass *vocal* cues to influence perceived credibility of the service robot. Therefore, perceived credibility, as a cognitive mechanism, only accounts for the positive effect of humanlike *language* instead of humanlike *voice*.

Interestingly, our finding is aligned with *employee voice* research in the hospitality literature that service staff’s *voice* has been consistently linked to positive emotions which in turn lead to behavioral intentions (e.g., revisit and WOM intentions) (Bartsch, 2008; Tsaur et al., 2015). It is noteworthy that previous studies on robotic *voice* were conducted either outside the service setting or in an unspecified setting. Hence, our study extends the robotic voice literature in a hospitality domain, suggesting that emotion is the primary mechanism accounting for the positive effect of humanlike *voice* of the service robot on diners’ consumption outcomes.

In this study, covariates such as respondents’ age, gender, and income levels do not influence their service encounter evaluation, revisit intentions and WOM intentions towards the restaurant. In previous research, consumers’ acceptance of service robots is found to vary across demographic factors (Chi, Denton, & Gursoy, 2020). However, studies in different service contexts have also suggested that customers’ willingness to use AI devices such as service robots is rather complex and conditioned by many factors such as user characteristics and the operating contexts (e.g., Conti et al., 2017; Hebesberger et al., 2017), which could be further influenced by customers’ perceptions and emotion generated during the interactional process (Chi et al., 2020). Therefore, our finding has again echoed previous research that calls for more context-specific examinations of robotic interactions given the intricacy of human robotic interaction and the critical role of the operating environment (e.g., Mende et a., 2019; Murphy et al., 2019).

5.1. Theoretical implications

First, findings of this study add evidence regarding the divergent and unsettled effect of anthropomorphism on customers’ service evaluation (e.g., Ferrari et al., 2016; van Pinxteren et al., 2019; Yu, 2019). Particularly, the present study identifies three principle humanlike attributes and pinpoints their effect on main consumption outcomes. These humanlike attributes are examined in a restaurant setting, a service context with intensive service interactions which is in more demand of service robots more than ever in time of a global pandemic (Seyitoğlu & Ivanov, 2020; Zeng et al., 2020).

More significantly, all three humanlike attributes co-exist and are evaluated simultaneously in our study. While anthropomorphism is proved to be a key determining factor for customers’ evaluation of HRI in hospitality, it has been mainly investigated either in a perceptual way (i.e., perceived anthropomorphism) (e.g., Lin et al., 2019; Qiu et al., 2019), or through a singular design feature with the predominant attention on the robot’s physical appearance (e.g., Choi et al., 2019; Zhu and Chang, 2020). Nonetheless, service encounter involves intertwined multisensory inputs that happen simultaneously and determine customers’ service evaluation together (Fink, 2012; Lee et al., 2019). In reality, it is never a single dimension of the frontline service actor’s outlook to decide a customer’s overall evaluation of the service interaction (Gustafsson et al., 2005). Therefore, the study extends the exiting literature of hospitality HRI by incorporating a multidimensional approach to unveil customers’ reaction to service robots when all the key anthropomorphic features are presented at the same time.

The results show that, when co-evaluated, *voice* and *language style* outplay the predominantly researched feature, *appearance*, to become the more crucial anthropomorphic factors. In addition, we uncovered an underlying mechanism that explains the influence of human-likeness on service evaluation through cognition and emotion. High levels of humanlike *voice* and *language style* can lead to positive emotions which in turn drive diners to appraise interactions with the robotic server more favorably. Robots paired with humanlike *language style* are perceived to be more reliable which accounts for the positive evaluation of the service encounter. Given the extremely limited research in hospitality and tourism analyzing the mediating process between anthropomorphism and consumption outcomes, our study made one of the first attempts on scrutinization of such process.

5.2. Managerial implications

This study culminates with several managerial implications. First, the findings of this study advise businesses to attend to the design features of AI-enable service robots. As customers tend to apply the human schema to for anthropomorphized objects (Choi et al., 2019), having humanlike *voice* and *language style* will likely help restaurants create a favorable interactional experience. Managers need to ensure desired attributes are programmed and tested before introduced onsite. Humanlike *language style* not only results in positive emotions but also enhances the perceived credibility of the robotic server, both of which are the fundamental reasons for a favorable encounter evaluation. Human-like *language style* is perceived to be more sincere, trustworthy, and dependable. It is important that restaurants leverage language programming features of service robots to elicit positive evaluations and repeat visits.

Drawing on the dominant effect of *voice* on all consumption outcomes, managers not only need to ensure high levels of humanlike *voice* when programming service robots but also integrate desired vocal features to further optimize customer perceptions. Luo et al. (2019) indicate that *voice* features such as less volatile amplitude and more stable speed can equip AI-chatbots with advantages that lead to greater customer satisfaction, long conversation, and greater sales. AI agents can also "learn" and simulate human conversation and voice features from high-performing human staff to enhance the human-likeness (Luo et al., 2019). Therefore, service managers may work with the manufacturing company for a customized *voice* programming.

Service managers should be aware that the positive effect of humanlike *voice* on WOM intentions is conditioned by the robotic server's degree of humanlike *appearance*. In other words, when the robotic server has high-levels of humanlike look (i.e., android), it is better to program the robot with low levels of humanlike *voice*. On the flip side, when service robots have a machine-like or medium level of humanlike *appearance*, the voice programming should feature high (vs. low) levels of humanlike *voice* for greater positive WOM intentions. With the advent of service automation and robotization in various tasks/functions in hospitality service encounters, findings of this study bestow marketing intelligence and prepare hospitality managers with relevant strategies to advance consumers experience and relationship with the business when robots are used for service interactions. According to interviews with restaurant customers, pleasant robot interactions may increase customer loyalty to the business (Qu et al., 2020). Despite the operational advantages of implementing service robots and reduced labor costs, automation in the frontline guest service requires businesses to clearly understand and manage factors that influence robotic interactions and the subsequent consequences. Hence, our research prompts useful insights for businesses to encourage revisit intentions and positive WOM intentions by carefully managing humanlike features of the service robot.

6. Limitations and future research

This study has several limitations. First, in this study we were only interested in post-consumption outcomes (e.g., service encounter evaluation, revisit intentions and WOM intentions) in response to robotic service interactions while dining out. We encourage future studies to continue to explore how various humanlike attributes of service robots can further influence diners' onsite behavior such as food choice, consumption volume, willingness to take suggestions from the robotic server, and time spent over the dining event. Although Mende et al. (2019) find that interaction with service robots induces compensatory eating, they also stress the necessity of examining the restaurant environment as it fosters social belongingness that alleviates increased consumption. Understanding onsite dining behavior will assist restaurants to manage guest experience with robotic server through development of new service protocols. Second, this study only tests a regular/satisfactory service encounter experience which may not be applicable the service fails to meet guests' expectations (e.g., service failure and recovery). It is worth investigating if high levels of human-likeness are still advantageous in response to service failure and providing recovery services. Third, in this study, we did not consider variations of the type (e.g., functional vs. hedonic) and the importance of tasks (e.g., core tasks vs. supporting tasks) performed by the robotic server and their varying impacts on consumer responses. Future studies may further investigate how the type of task and levels of importance can further add to the current dialogue for a deeper grasp of customer response to the robotic service.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at https://doi.org/10.1016/j.ijhm.2020.102823.

References

Bartneck, C., Kulić, D., Croft, E., Zoghbi, S., 2009. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. Int. J. Soc. Robot. 1 (1), 71–81.

Bartsch, S., 2008. What sounds beautiful is good?" How employee vocal attractiveness affects customer's evaluation of the voice-to-voice service encounter. In: Aktuelle Forschungsfragen Im Dienstleistungsmarketing (Current Research Questions in Service Marketing). Gabler, pp. 45–68.

Belk, R., 2016. Understanding the robot: comments on Goudey and Bonnin (2016). Rech. Appl. En Mark. 31 (4), 83–90.

Berezina, K., Ciftci, O., Cobanoglu, C., 2019. Robots, artificial intelligence, and service automation in restaurants. Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality. Emerald Publishing Limited.

Bischoff, R., Graefe, V., 1999. Integrating vision, touch and natural language in the control of a situation-oriented behavior-based humanoid robot. In: In IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No. 99CH37028), 2, pp. 999–1004.

Buhrmester, M., Kwang, T., Gosling, S.D., 2011. Amazon's mechanical Turk: a new source of inexpensive, yet high-quality, data? Perspect. Psychol. Sci. 6 (1), 3–5.

Burgers, A., de Ruyter, K., Keen, C., Streukens, S., 2000. Customer expectation dimensions of voice-to-voice service encounters: a scale-development study. Int. J. Serv. Ind. Manag. 11 (2), 142–161.

Choi, S., Liu, S.Q., Mattila, A.S., 2019. How may i help you?" says a robot: examining language styles in the service encounter. Int. J. Hosp. Manag. 82, 32–38.

Choi, Y., Oh, M., Choi, M., Kim, S., 2020. Exploring the influence of culture on tourist experiences with robots in service delivery environment. Curr. Issues Tour. https://doi.org/10.1080/13683500.2020.1735318.

Conti, D., Di Nuovo, S., Buono, S., Di Nuovo, A., 2017. Robots in education and care of children with developmental disabilities: a study on acceptance by experienced and future professionals. Int. J. Soc. Robot. 9 (1), 51–62.

Dautenhahn, K., Ghauoi, C., 2014. The Encyclopedia of Human-computer Interaction, 2nd ed. Interaction Design Foundation, Aarhus, Denmark.

Duffy, B.R., 2003. Anthropomorphism and the social robot. Rob. Auton. Syst. 42 (3-4), 177–190.

Edwards, C., Edwards, A., Stoll, B., Lin, X., Massey, N., 2019. Evaluations of an artificial intelligence instructor's voice: social Identity Theory in human-robot interactions. Comput. Human Behav. 90 (December 2017), 357–362.

Epley, N., Waytz, A., Cacioppo, J.T., 2007. On seeing human: a three-factor theory of anthropomorphism. Psychol. Rev. 114 (4), 864–886.

Eyssel, F., Kuchenbrandt, D., 2011, July. Manipulating anthropomorphic inferences about NAO: the role of situational and dispositional aspects of effectance motivation. In: 2011 RO-MAN. IEEE, pp. 467–472.

Eyssel, F., De Ruiter, L., Kuchenbrandt, D., Bobinger, S., Hegel, F., 2012, March. If you sound like me, you must be more human': on the interplay of robot and user features on human-robot acceptance and anthropomorphism. In: 2012 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, pp. 125–126.

Ferrari, F., Paladino, M.P., Jetten, J., 2016. Blurring human–machine distinctions: anthropomorphic appearance in social robots as a threat to human distinctiveness. Int. J. Soc. Robot. 8 (2), 287–302.

Fink, J., 2012, October. Anthropomorphism and human likeness in the design of robots and human-robot interaction. In: International Conference on Social Robotics. Springer, Berlin, Heidelberg, pp. 199–208.

Fong, T., Nourbakhsh, I., Dautenhahn, K., 2003. A survey of socially interactive robots. Rob. Auton. Syst. 42 (3-4), 143–166.

Gilbody-Dickerson, C., 2019, August 18. Restaurant Where Waiters Have Been Replaced With Female Robots. Metro. https://metro.co.uk/2019/08/18/restaurant-where-waiters-have-been-replaced-with-female-robots-10589560/.

Gockley, R., Forlizzi, J., Simmons, R., 2006, March. Interactions with a moody robot. Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction 186–193.

Goetz, J., Kiesler, S., Powers, A., 2003, November. Matching robot appearance and behavior to tasks to improve human-robot cooperation. In: The 12th IEEE International Workshop on Robot and Human Interactive Communication, 2003. Proceedings. ROMAN 2003. IEEE, pp. 55–60.

Goudey, A., Bonnin, G., 2016. Must smart objects look human? Study of the impact of anthropomorphism on the acceptance of companion robots. Rech. Appl. En Mark. 31 (2), 2–20.

Graefe, A., 2016. Guide to Automated Journalism. Tow Center for Digital Journalism. Columbia University. https://doi.org/10.7916/D80G3XDJ.

Gustafsson, A., Edvardsson, B., Nickson, D., Warhurst, C., Dutton, E., 2005. The importance of attitude and appearance in the service encounter in retail and hospitality. Managing Service Quality: An Int. J. 15 (2), 195–208.

Hebesberger, D., Koertner, T., Gisinger, C., Pripfl, J., 2017. A long-term autonomous robot at a care hospital: a mixed methods study on social acceptance and experiences of staff and older adults. Int. J. Soc. Robot. 9 (3), 417–429.

Ho, T.H., Tojib, D., Tsarenko, Y., 2020. Human staff vs. Service robot vs. Fellow customer: does it matter who helps your customer following a service failure

incident? Int. J. Hosp. Manag. 87, 102501 https://doi.org/10.1016/j.ijhm.2020.102501. Ahead of print.
Hosany, S., 2012. Appraisal determinants of tourist emotional responses. J. Travel. Res. 51 (3), 303–314.
Hutchinson, J., Lai, F., Wang, Y., 2009. Understanding the relationships of quality, value, equity, satisfaction, and behavioral intentions among golf travelers. Tour. Manag. 30 (2), 298–308.
Ivanov, S.H., Webster, C., 2017. Adoption of Robots, Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies–a Cost-benefit Analysis. Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies–A Cost-benefit Analysis.
Ivanov, S.H., Webster, C., Berezina, K., 2017. Adoption of robots and service automation by tourism and hospitality companies. Revista Turismo & Desenvolvimento 27 (28), 1501–1517.
Jensen, M.L., Averbeck, J.M., Zhang, Z., Wright, K.B., 2013. Credibility of anonymous online product reviews: a language expectancy perspective. J. Manag. Inf. Syst. 30 (1), 293–324.
Kim, Y., Kwak, S.S., Kim, M.S., 2011, July. The impact of robots language form on people's perception of robots. In: International Conference on Human Centered Design. Springer, Berlin, Heidelberg, pp. 253–261.
Kim, S.Y., Schmitt, B.H., Thalmann, N.M., 2019. Eliza in the uncanny valley: anthropomorphizing consumer robots increases their perceived warmth but decreases liking. Mark. Lett. 30 (1), 1–12.
Larivière, B., Bowen, D., Andreassen, T.W., Kunz, W., Sirianni, N.J., Voss, C., Wünderlich, N.V., De Keyser, A., 2017. Service Encounter 2.0": an investigation into the roles of technology, employees and customers. J. Bus. Res. 79, 238–246.
Lazarus, R.S., 1991. Cognition and motivation in emotion. Am. Psychol. 46 (4), 352.
Lee, K.M., Park, N., Song, H., 2005. Can a robot be perceived as a developing creature? Effects of a robot's long-term cognitive developments on its social presence and people's social responses toward it. Hum. Commun. Res. 31 (4), 538–563.
Lee, M., Lee, S.A., Koh, Y., 2019. Multisensory experience for enhancing hotel guest experience. Int. J. Contemp. Hosp. Manage. 31 (11), 4313–4337.
Lin, H., Chi, O.H., Gursoy, D., 2019. Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. J. Hosp. Mark. Manage. https://doi.org/10.1080/19368623.2020.1685053.
Lu, L., Cai, R., Gursoy, D., 2019. Developing and validating a service robot integration willingness scale. Int. J. Hosp. Manag. 80, 36–51.
Luna, N., 2020, January 23. Is Penny, the Robot Food Runner From Bear Robotics, Headed for Mass Production With Its $32M Investment Led by Softbank? Nation's Restaurant News. https://www.nrn.com/technology/penny-robot-food-runner-bear-robotics-headed-mass-production-its-32m-investment-led.
Luo, X., Tong, S., Fang, Z., Qu, Z., 2019. Frontiers: machines vs. humans: the impact of artificial intelligence chatbot disclosure on customer purchases. Mark. Sci. 38 (6), 937–947.
Markets and Markets, 2020. Service Robotics Market by Environment, Type (Professional and Personal & Domestic), Component, Application (Logistics, Inspection & Maintenance, Public Relations, Marine, Entertainment, Education, & Personal), and Geography—Global Forecast to 2025. Retrieved May 22 2020 from. https://www.researchandmarkets.com/reports/5004240/service-robotics-market-by-environment-type.
Mathur, M.B., Reichling, D.B., 2009, March. An uncanny game of trust: social trustworthiness of robots inferred from subtle anthropomorphic facial cues. In: 2009 4th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, pp. 313–314.
Matthews, K., 2020, April 26. Pandemic Proves Utility of a Wide Range of Service Robots. The Robot Report. https://www.therobotreport.com/pandemic-proves-utility-wide-range-service-robots/.
Mende, M., Scott, M.L., van Doorn, J., Grewal, D., Shanks, I., 2019. Service robots rising: how humanoid robots influence service experiences and elicit compensatory consumer responses. J. Mark. Res. 56 (4), 535–556.
Montoya, R.M., Horton, R.S., Vevea, J.L., Citkowicz, M., Lauber, E.A., 2017. A re-examination of the mere exposure effect: the influence of repeated exposure on recognition, familiarity, and liking. Psychol. Bull. 143 (5), 459–498.
Mori, M., 1970. The uncanny valley. Energy 7 (4), 33–35.
Murphy, J., Gretzel, U., Pesonen, J., 2019. Marketing robot services in hospitality and tourism: the role of anthropomorphism. J. Travel Tour. Mark. 36 (7), 784–795.
Nass, C.I., Brave, S., 2005. Wired for Speech: How Voice Activates and Advances the Human-computer Relationship. MIT press, Cambridge, MA.
Niculescu, A., van Dijk, B., Nijholt, A., Li, H., See, S.L., 2013. Making social robots more attractive: the effects of voice pitch, humor and empathy. Int. J. Soc. Robot. 5 (2), 171–191.
Perfect, T.J., Hunt, L.J., Harris, C.M., 2002. Verbal overshadowing in voice recognition. Appl. Cogn. Psychol. 16 (8), 973–980.
Phillips, E., Zhao, X., Ullman, D., Malle, B.F., 2018, February. What is human-like? Decomposing robots' human-like appearance using the anthropomorphic roBOT (ABOT) database. Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction 105–113.
Poliakoff, E., Beach, N., Best, R., Howard, T., Gowen, E., 2013. Can looking at a hand make your skin crawl? Peering into the uncanny valley for hands. Perception 42 (9), 998–1000.
Pouliot, L., 2016, September. Robots for Restaurants: the Future or Just a Gimmick? [PowerPoint Slides]. National Restaurant Association. https://www.restaurant.org/Downloads/Events/RIS/RIS/RIS16_robotics.
Prakash, A., Rogers, W.A., 2015. Why some humanoid faces are perceived more positively than others: effects of human-likeness and task. Int. J. Soc. Robot. 7 (2), 309–331.
Prentice, C., Dominique Lopes, S., Wang, X., 2020. The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. J. Hosp. Mark. Manage. https://doi.org/10.1080/19368623.2020.1722304.
Qiu, L., Benbasat, I., 2009. Evaluating anthropomorphic product recommendation agents: a social relationship perspective to designing information systems. J. Manag. Inf. Syst. 25 (4), 145–182.
Qiu, H., Li, M., Shu, B., Bai, B., 2019. Enhancing hospitality experience with service robots: the mediating role of rapport building. J. Hosp. Mark. Manage. 29 (3), 247–268.
Roseman, I.J., 2001. A model of appraisal in the emotion system. Appraisal Processes Emotion: Theory Methods Res. 68–91.
Ryu, K., Jang, S.C.S., 2007. The effect of environmental perceptions on behavioral intentions through emotions: the case of upscale restaurants. J. Hosp. Tour. Res. 31 (1), 56–72.
Seiter, J.S., Weger Jr, H., 2020. If memory serves: the effect of restaurant servers' memorization and muddling of orders. Int. J. Hosp. Manag. 84, 102320.
Shnabel, N., Purdie-Vaughns, V., Cook, J.E., Garcia, J., Cohen, G.L., 2013. Demystifying values-affirmation interventions: writing about social belonging is a key to buffering against identity threat. Pers. Soc. Psychol. Bull. 39 (5), 663–676.
Singer, R., 2016. Artificial Intelligence in the Hotel Industry. [PowerPoint slides]. Travelzoo. https://www.itb-convention.com/media/itbk/itbk_dl_en/itbk_dl_en_itbkongress/archive_2016/itb_hospitality_day_2/Robots_And_Artificial_Intelligence_In_The_Hotel_Industry_Singer.pdf.
Smith, C.A., Lazarus, R.S., 1993. Appraisal components, core relational themes, and the emotions. Cogn. Emot. 7 (3–4), 233–269.
Sugiura, K., Shiga, Y., Kawai, H., Misu, T., Hori, C., 2015. A cloud robotics approach towards dialogue-oriented robot speech. Adv. Robot. 29 (7), 449–456.
Surprenant, C.F., Solomon, M.R., 1987. Predictability and personalization in the service encounter. J. Mark. 51 (2), 86–96.
Tamagawa, R., Watson, C.I., Kuo, I.H., MacDonald, B.A., Broadbent, E., 2011. The effects of synthesized voice accents on user perceptions of robots. Int. J. Soc. Robot. 3 (3), 253–262.
Trovato, G., Ramos, J.G., Azevedo, H., Moroni, A., Magossi, S., Ishii, H., Simmons, R., Takanishi, A., 2015, August. Designing a receptionist robot: effect of voice and appearance on anthropomorphism. In: 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN). IEEE, pp. 235–240.
Tsaur, S.H., Luoh, H.F., Syue, S.S., 2015. Positive emotions and behavioral intentions of customers in full-service restaurants: does aesthetic labor matter? Int. J. Hosp. Manag. 51, 115–126.
Tung, V.W.S., Law, R., 2017. The potential for tourism and hospitality experience research in human-robot interactions. Int. J. Contemp. Hosp. Manage. 29 (10), 2498–2513.
Tussyadiah, I., 2020. A review of research into automation in tourism: launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism. Ann. Tour. Res. 81, 102883 https://doi.org/10.1016/j.annals.2020.102883. Ahead of print.
Tussyadiah, I.P., Park, S., 2018. When guests trust hosts for their words: host description and trust in sharing economy. Tour. Manag. 67, 261–272.
van Pinxteren, M.M., Wetzels, R.W., Rüger, J., Pluymaekers, M., Wetzels, M., 2019. Trust in humanoid robots: implications for services marketing. J. Serv. Mark. 33 (4), 507–518.
Walker, J.L., 1995. Service encounter satisfaction: conceptualized. J. Serv. Mark. 9 (1), 5–14.
Walters, M.L., Syrdal, D.S., Dautenhahn, K., Te Boekhorst, R., Koay, K.L., 2008a. Avoiding the uncanny valley: robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion. Auton. Robots 24 (2), 159–178.
Walters, M.L., Syrdal, D.S., Koay, K.L., Dautenhahn, K., Te Boekhorst, R., 2008, August. Human approach distances to a mechanical-looking robot with different robot voice styles. In: RO-MAN 2008-The 17th IEEE International Symposium on Robot and Human Interactive Communication. IEEE, pp. 707–712.
Wan, J., Aggarwal, P., 2015. Befriending Mr. Clean: the role of anthropomorphism in consumer-brand relationships. In: Fournier, S., Breazeale, M., Avery, J. (Eds.), Strong Brands, Strong Relationships. Routledge/Taylor & Francis Group, pp. 119–134.
Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S., Martins, A., 2018. Brave new world: service robots in the frontline. J. Serv. Manag. 29 (5), 907–931.
Yamada, Y., Kawabe, T., Ihaya, K., 2013. Categorization difficulty is associated with negative evaluation in the "uncanny valley" phenomenon. Psychol. Res. 55 (1), 20–32.
Yu, C.E., 2019. Humanlike robots as employees in the hotel industry: thematic content analysis of online reviews. J. Hosp. Mark. Manage. 29 (1), 22–38.
Zeng, Z., Chen, P.J., Lew, A.A., 2020. From high-touch to high-tech: COVID-19 drives robotics adoption. Tour. Geogr. 1–11. https://doi.org/10.1080/14616688.2020.1762118.
Zhang, T., Zhu, B., Lee, L., Kaber, D., 2008, August. Service robot anthropomorphism and interface design for emotion in human-robot interaction. In: 2008 IEEE International Conference on Automation Science and Engineering. IEEE, pp. 674–679.
Zhu, D.H., Chang, Y.P., 2020. Robot with humanoid hands cooks food better? Int. J. Contemp. Hosp. Manage. 32 (3), 1367–1383.
Złotowski, J., Proudfoot, D., Yogeeswaran, K., Bartneck, C., 2015. Anthropomorphism: opportunities and challenges in human–robot interaction. Int. J. Soc. Robot. 7 (3), 347–360.