

RESEARCH ARTICLE



Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The Humanness-Value-Loyalty model

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Abstract

Because of continuous improvements in their underlying technologies, customers perceive frontline robots as social actors with a high level of humanness, both in appearance and behavior. Advancing from mere theoretical contributions to this study field, this article proposes and empirically validates the humanness-value-loyalty model (HVL model). This study analyzes to what extent robots' perceived physical human-likeness, perceived competence, and perceived warmth affect customers' service value expectations and, subsequently, their loyalty intentions. Following two pretests to select the most suitable robots and ensure scenario realism, data were collected by means of a vignette experimental study and analyzed using the partial least squares method. The results reveal that human-likeness positively affects four dimensions of service value expectations. Perceived competence of the robot influences mainly utilitarian expectations (i.e., functional and monetary value), while perceived warmth influences relational expectations (i.e., emotional value). Interestingly, and contrary to theoretical predictions, the influence of the robot's warmth on service value expectations is more pronounced for customers with a lower need for social interaction. In sum, this study contributes to a better understanding of customers' reactions to artificial intelligence-enabled technologies with humanized cognitive capabilities and also suggests interesting research avenues to advance on this emerging field.

KEYWORDS

artificial intelligence, competence, frontline services, human-likeness, need for social interaction, robots, social categorization theory, warmth

1 | INTRODUCTION

In the past few years, robots and artificial intelligence (AI) technology have transformed many manufacturing and supply chain environments (Mariani & Borghi, 2019; Webster & Ivanov, 2020). Driven by

promises of cheaper customer service operations for a tech-savvy generation, the robots are now moving to the frontline of organizations to interact directly with customers. For instance, LoweBot guides customers through the Lowe's store and responds to their questions (Rafaeli et al., 2017), the Nao robot collaborates with bank

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tellers in some branches of the Bank of Tokyo (Belanche et al., 2020b), and some hotels feature robots performing hotel tasks such as check-in, luggage, and room service (Tussyadiah & Park, 2018; Tussyadiah et al., 2020).

Although using robots in production and warehousing facilities has clear and proven benefits, much less is known about the use of robots in frontline interactions with customers. Two nascent research lines provide some preliminary insights. First, some studies have focused on the capabilities of robots (Huang & Rust, 2018), how their technical features (e.g., sensors, chips, coding) facilitate their social interaction with people (Young et al., 2009), and how the cognitive or behavioral skills displayed by these robots drive users to see them as social actors (e.g. Broadbent, 2017; Moriuchi, 2020). Second, a stream of literature has specifically focused on robots' appearance (Tussyadiah & Park, 2018; Walters et al., 2008). As an important pillar in this study, the uncanny valley concept (Mori, 1970) proposes that people's attitude toward robots becomes more favorable as robots move from mechanical-looking to a human-like appearance, even though a slightly imperfect human-like robot may be perceived as eerie or uncanny.

Notwithstanding the progress made in these lines of research, several important knowledge gaps remain. Notably, most studies that focus on robots' "human" features overlook the marketing implications of the introduction of robot agents (Rosenthal-von der Püthen & Kramer, 2014) or are conducted in non-profit contexts such as elderly care (Čaić et al., 2018). As a result, customers' responses to such robots have not received much attention. Recent articles by Van Doorn et al. (2017), Wirtz et al. (2018) and Grewal et al. (2020) provide important conceptual contributions in this domain, but empirical work has been scarce (see Mende et al., 2019 for an exception). In addition, very few studies include both the robots' looks and their behavioral features. This omission is particularly noteworthy because customer responses in human-to-human frontline service interactions are influenced by the combination of employees' physical (e.g., attractiveness, obesity, etcetera) and nonphysical cues (e.g., King et al., 2006) and something similar may be expected in robot service delivery.

In response to these gaps in literature, this study proposes and empirically examines a new theoretical framework: the humanness-value-loyalty (HVL model). The HVL model investigates how customers' perceptions of robot humanness, considering the physical and behavioral features of the robot, affect service value and subsequently customers' loyalty intentions in frontline interactions. The model builds on social categorization theory (Eysel & Kuchenbrandt, 2012; Fiske et al., 2002), which states that individuals use visual and behavioral social cues to categorize an unknown person in a desirable or undesirable category. Although robots represent a novel category of agents in between human employees and self-service technology (Belanche, et al., 2020a), they are perceived by customers as social agents (Van Doorn et al., 2017). Previous theoretical frameworks such as computers are social actors (CASA, Nass & Moon, 2000; Reeves & Nass, 1996) already considered that humans treat machines as social agents but they ignored that the current advancements in

technology allow robots to actually look and behave as social agents in the frontline (Bartneck et al., 2009; Van Doorn et al., 2017).

Specifically, the HVL model proposes that robots' humanness features, that is, human-likeness in their appearance, and their competence and warmth, determine the expectations that customers hold towards the value being delivered in the service interaction. Focusing on humanness cues, literature on social cognition identifies competence and warmth as the two universal perceptions that drive people's impressions of persons (Fiske et al., 2007) and services (Güntürkün et al., 2020). Competence reflects the robot's ability to accurately and reliably perform a frontline task, which includes assessments of its intelligence, skill, and efficacy. Warmth is defined as a customer's judgment of whether a robot has good or bad intentions, which includes assessments of its friendliness, helpfulness, sincerity, trustworthiness, and morality (Fiske et al., 2007). In addition, the HVL model proposes that physical appearance is an essential element of social categorization (i.e., humanness perceptions). This assumption is based on previous literature on human–robot interaction (Kim et al., 2013; Walters et al., 2008) since technology users particularly attribute objects human mind-like abilities depending on the level of human-likeness (Krach et al., 2008; Rosenthal-von der Püthen & Kramer, 2014), where human-likeness is defined as the extent to which the robot's physical appearance is similar to a human being (Seyama & Nagayama, 2007).

Subsequently, the HVL model predicts that physical and behavioral robot cues influence service value expectations such that customers expect to derive greater value from robots with greater humanness. The focus on expectations is important as frontline robots may impress or surprise people compared to service delivery through employees or even self-service technologies (Roy & Sarkar, 2016). Such experiences of surprise may consume cognitive resources to the extent that individuals' cognitive processing of the service experience becomes more heuristic than systematic (Petty & Cacioppo, 1986). In these situations, expectations rather than perceptions become dominant in driving marketing outcomes such as customer loyalty (Habel, Alavi & Pick, 2017). Service value expectations reflect an anticipation of the utility of a service with regard to its functionality, social aspects, costs, and affectivity (Sweeney & Soutar, 2001; Zeithaml, 1988). Thus, based on service value expectation literature (Habel et al., 2016; Oliver et al., 1994), the HVL model proposes that expected service value should ultimately determine customers' loyalty intentions: the intent to continue using the service following the introduction of a service robot (Sirohi et al., 1998).

Previous studies also highlight the moderating role of individual traits in frontline innovation and technology adoption processes (e.g., Dabholkar & Bagozzi, 2002). Some customers prefer using technology-based service over traditional service because they find it easy to use, or it helps them avoid interaction with employees (Meuter et al., 2000). On the contrary, research shows that another set of customers prefers human interaction and avoids technology-based options (Dabholkar, 1996). These tendencies are captured by the individual trait 'need for social interaction', which is defined as the

importance of human interaction to the customer in service encounters. Need for social interaction may be especially important to understand customer reactions to service robots, given their capabilities of mimicking human cognition and behavior.

In sum, the HVL model developed in this study contributes to the advancement of theory on the service robots research field. First, the model focuses on robot's humanness, a concept widely neglected by previous works that considered robots to be just another new technology to adopt (Casey et al., 2020; Park & Kwon, 2016). The technological developments in automation and AI allow service robots to present higher levels of humanness in comparison to previous technologies (e.g., social presence, Van Doorn et al., 2017; greater intelligence, Huang & Rust, 2018). Advancing on recent insights that customers perceive technologies as social actors (Nass & Moon, 2000; Van Doorn et al., 2017), the humanness concept in the HVL model also adds detail to previous studies that focus on the robots' appearance as the prime source of their humanness (Tussyadiah & Park, 2018; Walters et al., 2008). Specifically, the model considers social categorization cues of warmth and competence to contribute to the frontline robots' overall humanness. Second, the HVL model links previous theoretical frameworks employed in the understanding of human–robot interaction (e.g. CASA, uncanny valley) to service value and relational marketing approaches, showing the practical impact of the introduction of robots in the frontline. Differently from research on robot adoption which frequently focused on customers' attitudes and acceptance of service robots (Gnambs & Appel, 2019; Murphy et al., 2019), the HVL model investigates how an increase in the different dimensions of robot humanness may affect customers' value expectations and loyalty intentions, two crucial variables in frontline services management (Wolter et al., 2017).

In the following, the literature review section describes the latest advances in this emerging research field and provides the theoretical underpinning of this current work. Following the hypotheses development, the methodology describes two pretests that serve to select the most suitable robots as stimuli to be used in the planned vignette study. A third pretest ensured desirable realism in the vignettes employed. Then data were collected among 526 US customers and analyzed using the partial least squares (PLS) method. The paper closes with the implications for scholars and practitioners to continue advancing on the understanding of this phenomenon.

2 | LITERATURE BACKGROUND

2.1 | Robots in the frontline

Sales of professional and entertainment-oriented service robots are currently increasing at a rate of 32% per year (International Federation of Robotics, 2020). Apart from contributing to performance enhancement (Sousa & Rocha, 2019), robots are expected to shake the employment horizon in the medium term (Edwards et al., 2017). Huang and Rust (2018) predict that robots will not only replace mechanical jobs, but also those involving analytical, intuitive and

empathetic skills. With the application of automation in the frontline, such as in retailing and customer service operations, the study of robots and AI has become an incipient field of research in marketing (Grewal et al., 2017; Ratchford, 2020). Much of the current contributions are conceptual in nature though.

For instance, Singh et al. (2017) use the complexity of the interactions (from simple to complex problem solving) and the richness of the interface (from efficient lean displays to more intelligent interfaces) to outline an interaction-based framework to describe various frontline interface technologies. Also Van Doorn et al. (2017, p. 43) explain how technology "continues to radically and rapidly change the nature of service, customer's service experiences, and customers' relationships with service providers." They propose a typology of technology infusions in frontline experiences based on the levels of human and automated social presence. Finally, Rafaeli et al. (2017) describe the need to clarify robots' capability to participate in social interaction and engagement compared to employees, and customers' possibility to establish personal connections to such technology.

2.2 | Service robots: A frontline agent between human employees and self-service technology

Service robots refers to "technology that can perform physical tasks (e.g., driving, housework, serving in a restaurant), operates autonomously without needing instruction, and is directed by computers without the help of people" (Colby & Parasuraman, 2016). In addition, Belanche et al. (2020a), identified that contrary to self-service technology, service robots may perform physical tasks as an employee would do and socially engage customers. This latter distinction is the most relevant one because previous technologies lack this capacity (Mende et al., 2019; Van Doorn et al., 2017). Frontline robots make customers feel that they are in the company of another social entity (Heerink et al., 2010).

Despite their social capabilities, service robots differ from human employees in many aspects. For instance, robots lack of intentionality and common ground with customers (Belanche et al., 2020a). Still, firms tend to give human features to other objects such as the personality of a brand (Coelho et al., 2020). Customers respond favorably to these features through a process called anthropomorphization (Guthrie, 1993; Mourey et al., 2017). For instance, Ivens et al. (2015) found that imbuing warmth and competence personality cues to brands affects customers' emotional responses.

2.3 | Social categorization cues: The relevance of robot humanness

Social categorization, a fundamental stream in social identity theory (Fiske et al., 2007), provides a solid basis to study individual's responses to human features of a novel social entity (i.e., a service robot). Following previous literature on social categorization, social

cognition, and human-robot interaction (cf., Cuddy et al., 2011; Rosenthal-von der Püthen, & Kramer, 2014), this study posits service robots' human-likeness, competence, and warmth as the three basic social cues that cognitively engage customers to assess the level of robot humanness and help them categorize a service robot as favorable or unfavorable.

Physical appearance represents a basic element in personal interaction between customers and frontline agents (Park et al., 2003). Focusing on technology, human-computer interaction follows the social rules of human-human interaction (Nass et al., 1995), especially when computers exhibit anthropomorphic cues that individuals use as a heuristic to apply socially-constructed rules (Grewal et al., 2020; Kim et al., 2013; Sundar, 2008). Previous literature places robots on an anthropomorphic appearance scale which varies from mechanical-looking to human-like appearance (Walters et al., 2008) and assumes that a more human appearance of a technological object increases people's accessibility of human schema because of human-like congruency (e.g., Aggarwal & McGill, 2007).

In addition, social cognition research identified competence and warmth as the two core universal dimensions of human impression formation (Cuddy et al., 2011; Fiske et al., 2007). This bidimensional framework springs from competence-incompetence and warm-cold favorability scales employed in social psychology to describe either interpersonal (Bales, 1950) or intergroup perceptions (e.g., stereotypes, Cuddy et al., 2007; Fiske et al., 2002). The two dimensions account for almost 80% of people's descriptions of a person in a first impression (Cuddy et al., 2011). In a frontline setting, Sirdeshmukh et al. (2002) describe how employees' behavioral cues of competence and benevolence (i.e., warmth) favor customers' trust, service value and loyalty to the firm in relational exchanges.

3 | THE HUMANNESS-VALUE-LOYALTY MODEL

The HVL model proposes that customers perceptions of robot's humanness are crucial for determining whether the service is advantageous and to shape the future relationship with the service provider. The HVL model posits that the (un)favorable categorization of robots based on their humanness shows in the value that customers anticipate to receive from a service. To further conceptualize service value, this study follows the commonly accepted Sweeney and Soutar (2001) framework (e.g., Petrick, 2002; Yang & Jolly, 2009), which identifies four dimensions of service value: (1) functional value, which reflects the expected utility derived from the quality and performance of the service; (2) social value, which reflects the expected utility derived from the service's ability to enhance social self-concept; (3) monetary value, which reflects the expected utility derived from the service due to the reduction of its perceived short term and longer term costs; (4) emotional value, which reflects the expected utility derived from the feelings or affective states that a service generates. In turn, a higher expected service value indicates to a customer that future benefits may be

derived from patronizing the service provider, which stimulates the intention to stay loyal to this particular firm (Zeithaml, 1988). The following set of research hypotheses thus proposes that expected service value mediates between service robots' humanness and customers' loyalty intentions.

3.1 | Robots' physical appearance: Human-likeness

Previous literature commonly proposes that people's acceptance of robots increases as a consequence of robot human-likeness (Walters et al., 2008). Because humanlike technological objects allow individuals to more easily access human congruence schemas (e.g., Aggarwal & McGill, 2007), robot human-likeness could be considered a factor analogous to physical appearance in humans. Psychology literature shows that anomalous or imperfect faces and bodies lead to negative social perceptions such as disgust and avoidance, usually based on stereotypes (Park et al., 2003; Zebrowitz & Montepare, 2008). Also advertising studies support clear positive effects of endorser's attractiveness on brand attitudes and purchase intentions (e.g., Till & Busler, 2000). Similarly, Ahearne et al. (1999) conclude that the attractiveness of a salesperson leads customers to attribute desirable traits to the salesperson such as likeability and trustworthiness. Employees' appearance consequently favors customers' responses involving expenditures such as tipping or purchasing more expensive products (Jacob & Guéguen, 2014; Otterbring et al., 2018). Finally, literature in services marketing shows that employees' appropriate physical appearance benefits customers' perceptions of service quality (Gronroos, 1984), firms' capabilities (Bitner, 1990), and encounter satisfaction (Mayer et al., 2003).

The HVL transfers the extant insights to the domain of frontline robots and hypothesizes that the human-likeness of frontline robots positively influences customers' expected service value. Specifically, when a robot looks more like a human being, customers infer human qualities from the robot (Aggarwal & McGill, 2007), such as a higher capability to adapt to customer's needs and demands (Belanche et al., 2020a) and a higher reliability because of experience (Gray & Wegner, 2012). Customers thus expect more functional value from a human-like robot. In addition, human-like robots are perceived as impressive, sophisticated, and reflecting state-of-the-art developments in the technological field (Roy & Sarkar, 2016). Such perceptions typically associate with the image of an innovation, which is a potent driver of its adoption because it facilitates users to gain social status (Moore & Benbasat, 1991). Human-likeness thus is likely to relate positively to expected social value.

Furthermore, customers usually infer that firms infuse technology in the frontline for cost reduction purposes, which negatively influences the value they derive from service interactions (Nijssen et al., 2016). However, when a robot has more human-like congruency, the "scripts" of service interactions (i.e., which actor conducts which task at what moment in time) more closely follow the traditional service encounter when compared to self-service technology (Broadbent et al., 2009; Tussyadiah & Park, 2018). This

requires less cognitive and behavioral adaptation on the customer side and deemphasizes any cost considerations (Belanche et al., 2020c). Robot human likeness may therefore positively relate to customers' expected monetary value. Finally, previous research has found that a more human-like robot creates a stronger sense of social presence, which is typically perceived as more enjoyable by customers (Heerink et al., 2010). Recent research in hospitality also found that robot anthropomorphism leads to customers' positive emotions (Murphy et al., 2019; Tussyadiah & Park, 2018). It is thus expected that robot human-likeness also relates positively to customers' expected emotional value. In sum, this study hypothesizes:

H1. *Customers' perception of the human-likeness of frontline robots positively influences (a) functional service value, (b) social service value, (c) monetary service value, and (d) emotional service value.*

3.2 | Robots' competence and warmth

Numerous studies on frontline employees describe how customers' perceptions of employee competence and benevolence affect service value (e.g., Bolton & Drew, 1991; Sirdeshmukh et al., 2002; Habel, Alavi, Schmitz, Schneider & Wieseke, 2016). In addition, literature on automation suggests that robots that demonstrate to be skillful in physical tasks and communicating with others are judged more positively by consumers (Bartneck et al., 2009).

The HVL model builds on these findings and suggestions and hypothesizes that customers' perceptions of frontline robots' competence positively relates to expected service value. More specifically, the perception of a frontline robot performing the promised service accurately and conscientiously constitutes an essential informational cue for inferring its functional value (cf., Habel et al., 2017; Liao & Chuang, 2004). In other words, if customers know that a robot does not make mistakes and provides a timely service, they will expect the robot-delivered service to be fulfilling their needs. In addition, people generally increase their social status when they feel part of a group that features successful others (Ashforth & Mael, 1989) or when they establish closer relationships with well-performing peers (Chinelato et al., 2021; Greenberg, 1988). A similar effect may occur in human–robot interaction. When interacting with an incompetent robot, customers may feel that they did not perform their service role well (cf., Meuter et al., 2005). On the contrary, interacting with a competent robot may make customers feel proud of themselves because they could coproduce the service using an innovative technology. A competent robot may thus enhance social value, too.

Previous literature also reports that customers are willing to pay more for services that are competently performed because it saves them time and effort in achieving the end results (cf., Homburg et al., 2005). Analogously, a competent robot makes customers perceive an enhanced notion of value-for-money, thus increasing expectations of monetary value. Along similar lines of reasoning, not having to worry about mistakes or negative consequences makes customers more

relaxed and likely to enjoy the service. It will this also increase the emotional service value. Thus, the following hypothesis is proposed:

H2. *Customers' perception of the competence of frontline robots positively influences (a) functional service value, (b) social service value, (c) monetary service value, and (d) emotional service value.*

Perceptions of warmth are relevant in frontline settings because such environments typically require a higher degree of interpersonal skills such as agreeableness, social perceptiveness, social orientation and active listening and speaking. Warmth judgements are made quickly and have a large impact on perceptions of others (Smith et al., 2016). Therefore, frontline employees' warmth (Habel et al., 2017), also known as courtesy (Babbar & Koufteros, 2008), civility (Kong & Jogaratnam, 2007) employee agreeableness (Liao & Chuang, 2004), benevolence (Sirdeshmukh et al., 2002) or empathy (Parasuraman et al., 1988), has been proposed as antecedent of service value. For robots, simple social behaviors, such as establishing eye contact or nodding the head as a sign of attention enhance perceptions of responsiveness and sympathy (Broadbent et al., 2009; Kanda et al., 2007), suggesting that social contact has been established (cf., Čaić et al., 2018).

The HVL model builds on these previous findings to hypothesize that customers' perception of a robot's warmth is positively related to their expected service value. To start, although functional value predominantly captures the reliability and efficiency of the service delivered, at least part of such perceptions are influenced by the social qualities displayed by the service provider (Bitner et al., 2000). Empathic service agents signal to customers that they have a genuine interest in understanding the customer (Morales, 2005), which may be needed to customize a service to fit specific customer needs (Bettencourt & Gwinner, 1996). As a result, perceptions of warmth may positively relate to functional value.

In addition, scholars have found that perceiving higher levels of warmth in another person develops feelings of admiration and approach behaviors (Cuddy et al., 2007; Fiske et al., 2007). In other words, "warm" others are typically desirable to be around and may appeal to one's self-esteem and status. A robot that is perceived as warm in nature may also enhance monetary value because the empathy in the service interaction may downplay potential customer attributions that the provider introduced the robot service because of cost and efficiency considerations (cf., Nijssen et al., 2016). The perceived warmth may communicate that the provider truly cares about its customers and this may trigger customer expectations of receiving value for money. Finally, warm frontline employees are considered as cooperative and caring for others (Bufquin et al., 2017). Translating these insights to a frontline robot, feelings of cooperation and personal care are likely to make a customer feel good and enjoy the service more. Warmth may thus positively relate to emotional value, too. This study therefore hypothesizes:

H3. *Customers' perception of the warmth of frontline robots positively influences (a) functional service value, (b) social service value, (c) monetary service value, and (d) emotional service value.*

3.3 | The influence of service value expectations on loyalty intentions

Offering service value to customers is a crucial aspect precondition for companies to be successful in the long run (e.g., Albrecht, 1992; Hartnett, 1998). Service value is based on the expectations or perceptions of what the customer gives and receives, thus reflecting an overall assessment of the utility of a service (Zeithaml, 1988). As a result, customers' decision-making may be driven by service value, so that greater service value will provide customers with a reason to stay loyal to the service provider (Sweeney & Soutar, 2001). In addition, in services that are more difficult to evaluate, service value expectations rather than perceptions shape customers' loyalty decisions (Habel et al., 2016). In other words, when individuals do not, or cannot, pay attention to the details of a service they make an assessment that is reflecting a so-called placebo effect. Because service robots may be impressive to customers, they may forget to thoughtfully consider the actual utility provided in the service encounter. Loyalty intentions are then formed in line with customers' expectations (Oliver et al., 1994). Taking into account the four service value dimensions, the HVL model hypothesizes that:

H4. (a) Functional service value, (b) social service value, (c) monetary service value, and (d) emotional service value positively influence loyalty intentions.

3.4 | The moderating effect of customer's need for social interaction

Need for social interaction varies greatly among customers (Dabholkar, 1996). For some customers, contact with a retail employee is very important, whereas for others it is not (Bitner et al., 1997). As a customer trait, need for social interaction is mostly considered a contingency factor (Dabholkar & Bagozzi, 2002; Schröder, 2007). Dabholkar and Bagozzi (2002) argue that customers with a greater preference for human interaction lack the intrinsic motivation to adopt the technological alternative to frontline employee, thus, they need to perceive more technological advantages to accept such change. Need for social interaction may thus be an important contingency factor in the proposed conceptual framework.

Specifically, this study posits that customers with a higher need for social interaction are more sensitive to increments in the human-likeness of robots because the technology-based service encounter then increasingly resembles the traditional service experience which they strongly prefer. In other words, the positive effects of human-likeness on service value will be especially important to customers with a high need for social interaction.

Furthermore, it is expected that need for social interaction moderates the effects of warmth, but not of competence, on service value. A competent robot does not make a service interaction more or less social per se. Although most people understand that a robot may be equally competent as a human, or may even make mistakes like a human, warmth is a characteristic that customers typically

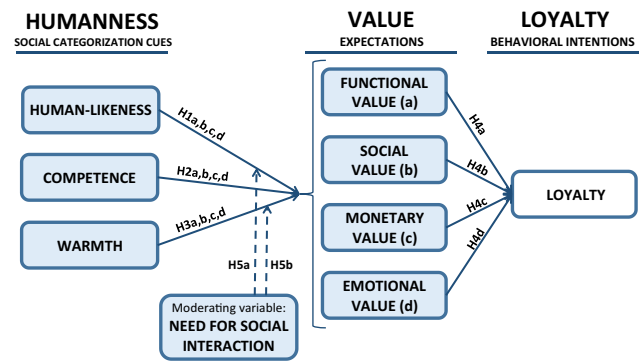


FIGURE 1 The HVL Model

attribute to a human being, not a robot (Broadbent et al., 2009). Especially customers with a high need for social interaction may be skeptical regarding the interactive qualities of technology (Dabholkar & Bagozzi, 2002). These individuals may therefore be especially surprised that a robot can display warmth in a service interaction. This may enhance the effect on what customers' expected service value. In sum, the last hypothesis proposes:

H5. Customer's need for social interaction strengthens the influences of robots' (a) human-likeness and (b) warmth perceptions on service value.

Although not hypothesized, the potential moderating effect of customer's need for social interaction on the relationship between perceived competence and service value was also included in the model for the sake of completeness. Figure 1 presents the HVL research model.

4 | METHODOLOGY

4.1 | Prestests on human-likeness for robot categorization and selection

Two pretests were conducted to select the most suitable stimuli for the planned vignette study. A first pretest was carried out to classify service robots on their level of human-likeness. A search for audio-visual material of robot prototypes or currently deployed service robots was started; 14 of them with supposedly different levels of anthropomorphism were selected (Rosenthal-von der Püthen & Kramer, 2014). This study only considered robots that may be used for providing services and did not select robots that can be used for other purposes such as domestic robots or small toy robots. Appendix 1 presents the pictures and names of the robots included.

To make an initial screening of robots, 116 US participants were recruited through a market research agency to participate in a robot categorization task. A total 64.7% of respondents were female; 13.8% of the respondents were below 25 years of age, 37.0% between 25 and 34 years, 34.5% between 35 and 44 years, and 14.7% were 45 years or over. Participants had to assign each of the

14 robots to one of the three theoretical categories of human-likeness proposed by Walters et al. (2008): (1) *Mechanoid*: a robot with a machine-like appearance and no overtly human-like features, (2) *Humanoid*: a robot which is not realistically human-like in appearance and is readily perceived as a robot by human, but possesses some stylized, simplified or cartoon-like human-like features (e.g., head, arms, eyes), or (3) *Android*: a robot which exhibits appearance which is as close to a real human appearance (including features such as hair, skin or teeth), humans may be fooled for a few seconds under carefully staged circumstances.

A picture of a robot not to be evaluated was shown as an initial example of each category. Furthermore, the names of the robots were not shown to participants to avoid potential branding effects and the order of robot presentation was randomized to avoid sequence effects.

Results of the pretest reveal customers' ability to distinguish between the three categories of robots with a very high percentage of agreement. In particular, K5 (97.4%) and Savioke (99.1%) were identified as mechanoids. Atlas (92.2%), HRP-4 (94.8%), Toro (95.7%), and Robothespian (96.6%) were identified as humanoids. In turn, Actroid (96.6%), Asuna (96.6%), Erica (96.6%), Geminoid (97.4%), Han (93.9%), Kodomoroid (96.6%), and Sophia (95.7%) were identified as androids. For robot HRP-4C, participants did not reach agreement since 59.5% of them identified it as an android and 39.6% identified it as belonging to the humanoid category. Thus, HRP-4C was discarded for the subsequent studies to avoid robot category conflict (Burleigh et al., 2013).

The next step was to establish how typical each robot was for its category, thus investigating differences in perceived human-likeness. A second pretest collected data among 91 students and non-students of a large European university (60.4% female) with ages ranging between 19 and 51 years ($M = 25.4$; $SD = 8.9$). Participants watched videos to assess each of the 13 robot's physical appearance. Each video was presented on a separate web page alongside the measurement scales. The video stimuli, presented in a randomized order, were used to ease the evaluation of the robots' features. To increase homogeneity, videos they had the same length (25 s), the same background music, and mainly showed the movements of the robot. Again, the name of the robots were hidden to avoid brand or name based evaluations.

Participants' assessed robots in terms of human-likeness using two items (human-like, mechanical-like) on a 7-point scale (1 "not at all" to 7 "very much"; Rosenthal-von der Püthen & Kramer, 2014). Participants were also asked whether they consider the robot to be eerie, to exclude from the vignettes those robots associated with creepiness.

The human-likeness ratings for all 13 robots (randomly presented) by all 91 participants resulted in 1183 evaluations, with some missing values. Table 1 shows the descriptive statistics for each robot. Consistent with the former pretest, less human-like robots are those previously categorized as mechanoids: K5 and Savioke. Humanoids reach intermediate levels of human-likeness: Toro, Atlas, HRP-4 and Robothespian. In turn, Androids present

TABLE 1 Descriptive statistics

Category	Robot	Human-likeness	
		M	SD
Mechanoid	K5	1.264	0.899
Mechanoid	Savioke	1.319	0.845
Humanoid	Toro	1.830	1.111
Humanoid	Atlas	1.901	1.014
Humanoid	HRP-4	1.934	1.070
Humanoid	Robothespian	2.390	1.245
Android	Han	4.494	1.242
Android	Sofia	5.294	1.218
Android	Actroid	5.495	1.309
Android	Kodomoroid	5.657	1.091
Android	Asuna	5.758	1.148
Android	Erica	5.783	1.195
Android	Geminoid	6.302	1.105

TABLE 2 Between groups differences for human-likeness

Robot groups	Mechanoids		Humanoids		Androids	
	M	SD	M	SD	M	SD
Human-likeness	1.291	0.039	2.014	0.255	5.541	0.556

the higher levels of human-likeness: Han, Sofia, Actroid, Kodomoroid, Asuna, Erica, and Geminoid. Toro and Han were identified as eerie robots by 27 and 32 participants, respectively, providing evidence that they should be excluded in the subsequent study. Finally, differences in human-likeness were tested across the three groups of robots. Table 2 shows the mean and standard deviation for human-likeness ratings of the robots in each category. Results of an ANOVA confirmed significant differences between categories ($F = 113.379$, $p < 0.01$).

One prototypical robot of each category was selected to be used in the main study. This selection was made based on the results of the two pretests and the specific needs of the main study setting (e.g., having a full body to carry out waiter tasks). Considering this information, K5, HRP-4 and Geminoid were selected as the suitable prototypical examples of mechanoid, humanoid and android categories, respectively.

4.2 | Main study

The main study featured a vignette that introduced a frontline robot named Casey performing waiter tasks (e.g., taking orders, providing meal advice). This setting was selected because many frontline employee studies have been conducted in restaurant contexts

(Kong & Jogaratnam, 2007; Liao & Chuang, 2004), and robot waiters are already serving customers in several restaurants around the world. Participants were invited to read a general introduction which included a full body picture of K5 (low human-likeness, mechanoid), HRP-4 (medium human-likeness, humanoid), or Geminoid (high human-likeness, android). The use of pictures instead of videos avoided any bias due to video incongruence with the waiter task setting. To ensure that loyalty intentions could be reliably measured, the introduction asked participants to consider a real and well-known mid-class restaurant where they have been dining several times before. Following the introduction, competence and warmth were manipulated in line with Cuddy et al. (2007) and Funk (1996). To ensure that service value expectations rather than perceptions could be measured, participants read that they learned about the robot's service through a local newspaper article, and through a friend who recently visited the restaurant. Thus, participants were *not* told to imagine themselves in the restaurant. Appendix 2 reports the full vignette descriptions.

A pre-test with 156 US participants recruited through a market research agency was performed to ensure the correct description of each condition and to evaluate scenario realism. To this end, two items ("The scenario is realistic", "The scenario is believable") were used (Bagozzi et al., 2016). The results confirmed the suitability of the scenario since the two items ($\alpha = 0.96$) provided a mean of 4.53 and an SD of 1.71, which is significantly greater than 4—the central point of the scale—($t = 3.88, p < 0.01$), indicating that participants perceived the robot waiter scenario as realistic and believable.

The main study sample featured 526 US customers recruited through a market research agency. A number of 53.2% of the participants were female, 6.8% of the respondents were below 25 years of age, 38.0% between 25 and 34 years, 26.8% between 35 and

44 years, 14.8% between 45 and 54 years, and 13.5% of the participants were 55 years or over. Participants received a fee for completing the survey. They were randomly assigned to each of the 12 robot conditions resulting from a 3 (mechanoid, humanoid, android) $\times$ 2 (high competence vs. low competence) $\times$ 2 (high warmth vs. low warmth) experimental design, with 41 to 48 participants per condition.

4.2.1 | Measurement scales and validation

Participants' were asked to assess the robots in terms of human-likeness, competence and warmth, as well as their expectations of service value and their loyalty intentions. Specifically, human-likeness was measured using the same two-item scale as in the pretest. Five items borrowed from Cuddy et al. (2004) and Fiske et al. (2002) were used to measure perceived competence (skillful, efficient, intelligent, competent and competitive) and warmth (good-natured, sincere, warm, trustworthy and tolerant). Participants rated each robot with regard to these items on a 7-point scale from 1 "not at all" to 7 "very much".

The four dimensions of service value were measured with 19 items adapted from Yang and Jolly (2009) and Sweeney and Soutar (2001), reported in Table 3. Four items Ryu et al. (2012) and Yang and Jolly (2009) served to measure loyalty intentions. These items used 7-point Likert scales (1 = *strongly disagree*, 7 = *strongly agree*) and included "I would like to come back to this restaurant in the future," "I would consider revisiting this restaurant in the future," "Given the chance, I intend to use this kind of robot service," and "I expect my use of robot service to continue in the future." Finally, need for social interaction was measured using the four-item scale of Dabholkar and

TABLE 3 Service value measurement

Functional value	<i>I think that the robot based service would...</i>	Monetary value	<i>I think that the robot based service would...</i>
FVALUE1	be reliable	MVALUE1	be good for the price
FVALUE2	function well	MVALUE2	be reasonable priced
FVALUE3	be well provided	MVALUE3	be economical
FVALUE4	be provided in a timely manner	Emotional value	I think that using the robot service would...
FVALUE5	fulfill my needs well	EVALUE1	make me feel relaxed
FVALUE6	offer consistent quality	EVALUE2	make me feel good
Social value	<i>Me using the robot service would...</i>	EVALUE3	be enjoyable
SVALUE1	make me feel accepted by others	EVALUE4	give me pleasure
SVALUE2	make a good impression on other people	EVALUE5	be interesting
SVALUE3	give me social approval	EVALUE6	make me want to use it
SVALUE4	improve the way I am perceived by others		

Bagozzi (2002): "Human contact in providing services makes the process enjoyable for the consumer," "I like interacting with the person who provides the service," "Personal attention by the service employee is very important to me," and "It bothers me to use a machine when I could talk to a person instead."

4.2.2 | Manipulation checks

Table 4 indicates that the assessment of whether the three types of robots differed in their human-likeness led to results similar to those in the second pretest. Differences were significant among the three groups. Then, it was confirmed that perceived competence was significantly higher in the high-competence condition than in the low-competence one ($M_{\text{High-Competence}} = 5.00$, $M_{\text{Low-Competence}} = 3.48$, $t = 13.44$, $p < 0.01$). Finally, it was confirmed that perceived warmth was significantly higher in the high-warmth condition than in the low-warmth one ($M_{\text{High-Warmth}} = 4.24$, $M_{\text{Low-Warmth}} = 2.88$, $t = 10.07$, $p < 0.01$). These results confirm a successful manipulation for perceived human-likeness, warmth and competence. In further analyses, warmth and competence are introduced as dummy variables representing high (1) versus low (0) levels. Since human-likeness has three categories and the differences among them are not equivalent, the scale of perceived human-likeness is used to test the research model.

4.2.3 | Analytical procedure and measure validation

Hypotheses of the HVL model were tested with PLS structural equation modeling (SEM) because it is especially useful when the phenomenon under research is relatively new (Roldán & Sánchez-Franco, 2012). Since the main goal of this study is predictive (i.e., to predict service value and loyalty intentions), the selection of PLS is also appropriate because, as a variance-based rather than covariance-based SEM method, it provides optimal predictive power (e.g., Bagozzi, 1994; Fornell & Bookstein, 1982). In addition, PLS modeling is particularly useful for testing complex models including several indirect and moderating effects at the same time (Davcik, 2014), as in this study. Data analyses were carried out using SmartPLS software version 3.0 (Ringle et al., 2015).

To assess the validity of the measurement model, construct reliability was first evaluated. In this respect, all item loadings exceeded the recommended value of 0.7 (Henseler et al., 2009). Similarly, both the Cronbach's α and the composite reliability of each construct exceeded the 0.7 thresholds (Nunnally & Bernstein, 1994), supporting their

reliability. Furthermore, the average variance extracted (AVE) of each construct exceeded the recommended threshold of 0.5 (Hair et al., 2013), confirming the constructs' convergent validity. Furthermore, the outcomes of three procedures confirmed the discriminant validity of the concepts. First, Table 5 confirms that the square root of the AVE for each construct exceeded the correlation among variables (Fornell & Larcker, 1981). Second, the Heterotrait-Monotrait Ratio (HTMT) of the correlations between variables were below the 0.9 threshold for all cases (Hair et al., 2017; Henseler et al., 2015). Third, the cross-loadings confirmed that, for each variable, the loadings of their indicators were higher for their corresponding construct than for other variables (cf., Hair et al., 2011).

Finally, the standardized root-mean residual (SRMR) was calculated as an indicator of global model fit. The SRMR of the research model is 0.05, which indicates good model fit as it is lower than the 0.08 threshold (Hu & Bentler, 1998). In addition, the normed fit index (NFI) of the research model is 0.89, which is close to the recommended 0.90 (Hu & Bentler, 1998).

4.2.4 | Results

To test the hypotheses a bootstrapping procedure with 5000 subsamples was employed (Hair et al., 2011; Hair et al., 2017). To test the moderating effects proposed in H5a and H5b, the orthogonalizing technique allowed to remove the linear information of the interaction term associated with the main effect indicators (Little et al., 2006). Table 6 presents the results.

Human-likeness shows a significant positive relationship with all service value expectations (i.e., functional, social, monetary, and emotional value). Therefore, H1a-d are supported. Second, competence exerts a positive significant effect on all service value expectations, except for social value. These results confirm H2a, H2c and H2d, but H2b is not supported. In turn, warmth has a positive significant effect on emotional value, confirming H3d, but not on functional, social and monetary value, so H3a-c are not supported. Interestingly, perceived competence has the greatest effect on functional value and monetary value (more utilitarian in nature), and perceived warmth has the greatest effect on emotional value (more relational in nature). Finally, regarding the influence of service value expectations on loyalty intentions, H4a, H4c and H4d are confirmed as functional, monetary, and emotional value positively and significantly influence loyalty intentions. However, the influence of social value on loyalty intentions is not significant, such that H4b cannot be not supported.

TABLE 4 Manipulation check of human-likeness

Robot	Mechanoid (N = 176)		Humanoid (N = 175)		Android (N = 169)		F	p
	M	SD	M	SD	M	SD		
Human-likeness	1.881	1.021	2.557	1.179	5.071	1.276	358.72	0.000*

*Significant at $p < 0.01$.

TABLE 5 Convergent and discriminant validity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Cronbach's α	CR	AVE
1. Human-likeness (1)	0.866	0.022	0.132	0.208	0.263	0.124	0.198	0.164	0.076	0.744	0.855	0.751
2. Perceived competence (2)	0.027	1	0.019	0.442	0.057	0.222	0.128	0.144	0.032	1	1	1
3. Perceived warmth (3)	0.116	0.019	1	0.088	0.037	0.024	0.160	0.090	0.068	1	1	1
4. Functional value (4)	0.218	0.434	0.116	0.919	0.509	0.772	0.682	0.691	0.164	0.963	0.970	0.845
5. Social value (5)	0.286	0.056	0.037	0.493	0.955	0.528	0.671	0.575	0.140	0.968	0.976	0.912
6. Monetary value (6)	0.137	0.216	0.024	0.732	0.505	0.937	0.675	0.691	0.132	0.931	0.956	0.879
7. Emotional value (7)	0.208	0.125	0.155	0.653	0.645	0.635	0.883	0.891	0.285	0.942	0.955	0.780
8. Loyalty intentions (8)	0.171	0.140	0.088	0.664	0.554	0.653	0.847	0.940	0.324	0.956	0.968	0.884
9. Need for social interaction (9)	-0.021	-0.014	0.061	-0.175	-0.139	-0.142	-0.282	-0.326	0.872	0.900	0.927	0.760

Note: Diagonal elements (bold figures) are the square root of the AVE (the variance shared between the constructs and their measures). Below-diagonal elements are the correlations among variables. Above-diagonal elements (in italics) are HTMT values. Abbreviations: AVE, average variance extracted; CR, composite reliability.

Furthermore, customers' need for social interaction significantly strengthens the influence of human-likeness on functional value and emotional value. This provides partial support to H5a. Remarkably, the need for social interaction weakens rather than strengthens the influence of perceived warmth on both social and emotional value. The need for social interaction does not moderate the relationship between warmth, functional value, and monetary value. In sum, H5b is not supported. In line with the conceptual argumentation for not formulating an interaction hypothesis with regard to perceived competence, results show that need for social interaction indeed does not alter the effects of competence on service value expectations.

Additionally, an analysis of variance (ANOVA) was carried out to better understand the counterintuitive attenuating effect of customers' need for social interaction on the relationships between robot warmth on social and emotional value. Following the standard procedure to compare between groups, customers with high and low need for social interaction were split on the average of their scores on this measure (Belanche et al., 2017). Results of these analyses corroborate the findings. As Figure 2 shows, the interaction effect is significant for social value ($F = 3.94$; $p < 0.05$), robot's warmth has a positive influence on social value among customers with a low need for social interaction; however, this influence turns negative among customers with high need for social interaction. Focusing on emotional value as the dependent variable, the interaction effect is also significant ($F = 6.78$; $p < 0.01$). In this case, robot's warmth exerts a clear positive effect on emotional value among customers with low need for social interaction, but this positive influence almost disappears for customers with a higher need for social interaction as depicted in Figure 3. These findings are discussed in more detail in the discussion section.

Finally, the mediating role of the service value dimensions was evaluated. Following Chin (2010) and Zhao et al. (2010), bias-corrected confidence intervals of indirect effects were calculated, using 5000 subsamples with no sign change. Table 7 shows that

perceived human-likeness (confidence interval: 0.105–0.240), warmth (confidence interval: 0.028–0.174) and competence (confidence interval: 0.097–0.253) only indirectly influence loyalty intentions. Perceived human-likeness and competence influence loyalty intentions through functional, monetary and emotional values, while warmth influences loyalty intentions through emotional value. The existence of these indirect effects constitutes sufficient evidence of fully mediated relationships (Zhao et al., 2010). Perceived human-likeness and competence have a significant total effect on loyalty intentions, whereas the total effect of warmth on loyalty intentions is nonsignificant.

5 | DISCUSSION

Apart from increasing productivity and profitability in manufacturing, innovation in robotics is increasingly transforming service interactions (Grewal et al., 2017; Van Doorn et al., 2017). However, so far little empirical work has been conducted on robots in the frontline and important insights in role of the robot's "human" features were yet to be uncovered. Based on social categorization and social cognition theory, the HVL model contributes to clarify to what extent robot humanness cues motivate customers to categorize the robot service agent as valuable, and thus affect the customer experience. More specifically, this study finds that the robot's physical human-likeness increases customers' expectations of service value in four domains: functional value, social value, monetary value, and emotional value. In addition, the perceived competence of the robot also plays a relevant role since it influences mainly utilitarian expectations (i.e., functional and monetary value) but also emotional value. In turn, perceived warmth only influences a relational expectation (i.e., emotional value). Furthermore, while competence appears as a universal driver of customer service value, the effects of human-likeness and warmth depend, at least partially, on customers' need for service interaction. These value expectations fully mediate the effect of

TABLE 6 Research model: Direct and moderating effects

Predictors	Dependent Variables											
	Service Value Expectations						Loyalty Intentions					
	Functional			Social			Monetary			Emotional		
	β	t	p	β	t	p	β	t	p	β	t	p
Human-Likeness (HL)	0.197**	5.415	0.000	0.277**	7.000	0.000	0.128**	3.125	0.002	0.179**	4.480	0.000
Perceived Competence (PC)	0.428**	12.344	0.000	0.048	1.160	0.246	0.207**	5.004	0.000	0.112**	2.850	0.004
Perceived Warmth (PW)	0.069	1.863	0.063	0.013	0.322	0.748	0.012	0.286	0.775	0.150**	3.821	0.000
Functional Value	-	-	-	-	-	-	-	-	-	-	-	-
Social Value	-	-	-	-	-	-	-	-	-	-	-	-
Monetary Value	-	-	-	-	-	-	-	-	-	-	-	-
Emotional Value	-	-	-	-	-	-	-	-	-	-	-	-
Need for Social Interaction (NSI)	-0.169**	4.230	0.000	-0.133**	3.038	0.002	-0.137**	3.115	0.002	-0.286**	6.849	0.000
HL x NSI	0.187**	4.139	0.000	0.123	1.891	0.059	0.186	1.379	0.168	0.176*	2.015	0.044
PC x NSI	0.043	0.631	0.528	-0.030	0.461	0.645	-0.028	0.478	0.633	-0.027	0.423	0.672
PW x NSI	-0.113	1.105	0.269	-0.094*	1.962	0.050	-0.081	0.989	0.323	-0.136**	3.466	0.001
R ²	0.309			0.125			0.122			0.203		0.755

*Significant at $p < 0.05$.

**Significant at $p < 0.01$.

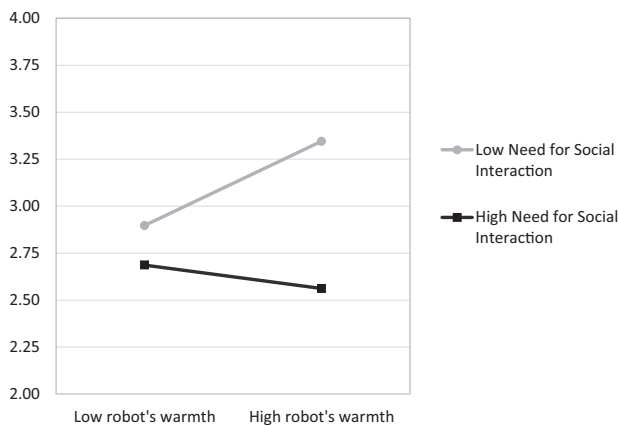


FIGURE 2 Interaction effect of perceived warmth and need for social interaction on social value

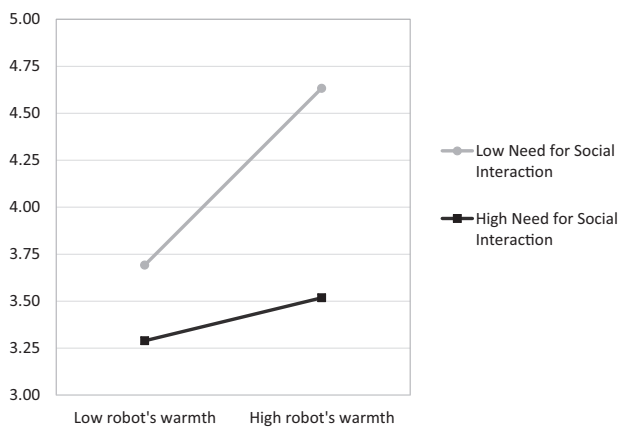


FIGURE 3 Interaction effect of perceived warmth and need for social interaction on emotional value

robot humanness on loyalty intentions, showing the need to integrate service value in future marketing research on service robot.

5.1 | Theoretical implications

The HVL model and its empirical validation make several important contributions to literature. From a theoretical approach, the HVL is built on the core idea of robot humanness as a concept entailing both physical and nonphysical features. As far as service robots are social agents with social presence and highly developed skills sometimes exceeding human intelligences (Huang & Rust, 2018; Van Doorn et al., 2017), this study combines previous theoretical streams of human-robot interaction and social categorization and cognition theories. The HVL model expands the concepts of robot's anthropomorphism (i.e. human-likeness, Rosenthal-von der Püthen & Kramer, 2014) with a social categorization perspective (Cuddy et al., 2007; Fiske et al., 2007). So far insights on the behavior and actions of robots has been embedded in research on AI (Broadbent, 2017; Young et al., 2009), while insights on customers' reactions to the

anthropomorphic appearance of robots have been developed in a different line of inquiry (Tussyadiah & Park, 2018; Walters et al., 2008). This study does not only connect these research lines, it also delivers empirical rather than conceptual support, investigates marketing-relevant outcomes of robots in the frontline, and extends insights on self-service technology which does not account for robots' unique AI-driven characteristics, autonomous operation, and interactive skills (Colby & Parasuraman, 2016).

This study also adds to recent work on customer-robot encounters which focuses on customers' perceptions about robot-produced outcomes, such as the usefulness of this technology (Belanche et al., 2020a; Moriuchi, 2020) but that often ignore customers' perceptions of service robots as social agents. Furthermore, the HVL model advances in several theoretical frameworks currently employed in the understanding of human-robot interaction in the service domain. For instance, robot humanness could be considered a more encompassing concept compared to the notion of robotic social presence (van Doorn et al., 2017), an aspect of increasing interest in frontline service interactions. In addition, in line with the theoretical works of Huang and Rust (2018) explaining how automated intelligence adds to or even beats human intelligence, the current study reveals that customers' perceptions of a higher robot humanness differentially relate to four different value expectations. This paper's contribution to integrate individuals' perceptions of service robots and their related value expectations and loyalty intentions also enriches several new streams of literature that take a rather narrow approach by analyzing specific features, such as the realism maximization theory, which focuses on natural language processed and produced by AI (Cherif & Lemoine, 2017; Moriuchi, 2020) or CASA, which focuses on the technology development of reciprocity and personality traits (Nass & Moon, 2000).

Focusing on the empirical findings, most studies in marketing argue that customers generally value competence more than warmth in human-to-human service encounters because they pursue task-related goals in their relationships with service providers (Güntürkün et al., 2020). The current study corroborates this finding in a robot-to-human service context, and at the same time provides the nuance that neither robot competence nor warmth provides any social value. It is another social cue, the physical human-likeness, that drives people's perceptions that using the robot makes a good impression on others. Contributing to the debate of the uncanny valley existence, this result suggests that, despite any potential threat perception (Mende et al., 2019), a high level of human-likeness in a service robot increases the social value for the customer. This finding also resonates with seminal insights in technology adoption literature that the image of an innovation makes adopters feel positive, because they like others to see them using the innovation as it facilitates users to gain social status (Moore & Benbasat, 1991).

A particularly noteworthy finding is the fact that this study proposed that individuals with a preference for human contact would value the robot's warmth more, but the results indicate the opposite. This contraindication may be explained by Gray and Wegner (2012); they state that people prefer robots with higher anthropomorphism

TABLE 7 Indirect and direct effects of social categorization cues on loyalty intentions

	Estimate	95% Bias confidence interval	t	p
Indirect total effects				
Human-likeness → Loyalty intentions	0.172**	(0.105, 0.240)	4.940	0.000
Perceived Competence → Loyalty intentions	0.173**	(0.097, 0.253)	4.287	0.000
Perceived Warmth → Loyalty intentions	0.101**	(0.028, 0.174)	2.714	0.007
Direct effects				
Human-likeness → Loyalty intentions	-0.012	(-0.056, 0.032)	0.539	>0.1
Perceived Competence → Loyalty intentions	-0.038	(-0.091, 0.010)	1.479	>0.1
Perceived Warmth → Loyalty intentions	-0.034	(-0.077, 0.010)	1.494	>0.1
Total effects				
Human-likeness → Loyalty intentions	0.160**	(0.082, 0.241)	3.913	0.000
Perceived Competence → Loyalty intentions	0.135**	(0.050, 0.217)	3.167	0.000
Perceived Warmth → Loyalty intentions	0.067	(-0.016, 0.152)	1.559	>0.1
Specific indirect effects				
HL → FV → LOY	0.031**	(0.012, 0.056)	2.799	0.005
HL → SV → LOY	-0.007	(-0.024, 0.008)	0.911	>0.1
HL → MV → LOY	0.016*	(0.003, 0.033)	2.079	0.038
HL → EV → LOY	0.132**	(0.077, 0.191)	4.565	0.000
PC → FV → LOY	0.066**	(0.028, 0.112)	3.120	0.002
PC → SV → LOY	-0.001	(-0.006, 0.002)	0.620	>0.1
PC → MV → LOY	0.026*	(0.008, 0.047)	2.581	0.010
PC → EV → LOY	0.082**	(0.023, 0.141)	2.776	0.006
PW → FV → LOY	0.009	(-0.003, 0.023)	1.303	>0.1
PW → SV → LOY	0.000	(-0.004, 0.003)	0.047	>0.1
PW → MV → LOY	0.001	(-0.010, 0.012)	0.106	>0.1
PW → EV → LOY	0.092**	(0.034, 0.151)	3.080	0.002

Abbreviations: EV, emotional value; FV, functional value; HL, human-likeness; LOY, loyalty intentions; MV, monetary value; PC, perceived competence; PW, Perceived warmth; SV, social value.

*Significant at $p < 0.05$.

**Significant at $p < 0.01$.

and those that are good at performing physical tasks (i.e., human-likeness and competence, respectively). However, people feel uneasy when they perceive that robots feel and sense as humans do. Hence, especially for people that enjoy social interaction with humans, experiencing the warmth of a robot may feel uneasy. This finding suggests that previous theoretical insights about the existence of the uncanny valley might not solely apply to perceptions about robot's physical appearance but also to perceptions about robot's capability to think and feel as a human (cf., Gray & Wegner, 2012). This finding may be also related to recent studies about the growth of robot unpopularity in society, particularly in the workplace (Gnambs & Appel, 2019). Perhaps robots do not need to have social skills as

humans do (warmth, empathy, sense of humor), but may rather incorporate less sophisticated affective abilities that are valued in a specific context (Valdez Cervantes & Franco, 2020), such as the pet robots providing company to the elderly (Bemelmans et al., 2015)

5.2 | Managerial implication

As a fundamental outcome of the HVL model, service providers are advised to introduce robots with higher levels of humanness since these features contribute to increase customers loyalty intentions, an effect fully mediated by service value expectations. While service

managers who are looking to add robots to their frontline operations may think that the looks of a robot do not really matter to customers, the results of this study underscore the importance of investments in robots that resemble humans. First, the categorization of robots as mechanoids, humanoids and androids offers much possibilities to designers, engineers, and marketers to experiment with robots with different levels of human-likeness and select the robot that best fits their purposes. Second, robot human-likeness influences both utilitarian and relational value that customers may derive from service encounters and thus, ultimately, provides the most potent lever to control customer loyalty intentions. The results of the study suggest that service providers could introduce robots with a more human appearance to help customers make a good impression on others. Due to their novelty and “humanness,” human-like frontline robots would increase the attractiveness of the establishments they operate in and enhance people’s curiosity about the innovation. Being aware of this advantage, restaurant managers should favor this positive social buzz by allowing customers to take photos of/with the robots and posting them in social media (Babin & Hulland, 2019; Gracia et al., 2012). The investment in service robots’ human-likeness and competence may also benefit the price image of the store and thus help to build a price fighter image.

Focusing on the emotional value expectations, the research found that the three dimensions of humanness affect to this service value. That is, to engage customers affectively, service providers should introduce robots with high human-likeness, competence and warmth features. This result is in line with the theory of AI job replacement, which suggests that service robots will need highly sophisticated skills to replace employees in complex service interactions (Huang & Rust, 2018).

Through the analysis of the contextual effects of customers’ need for social interaction, this study also provides interesting insights toward market segmentation. When serving a customer base that has a high need for social interaction, the ideal robot looks human-like but warmth is less valued; suggesting that customers-employee human touch cannot be replaced by human-robot parasocial interactions. Although the need for social interaction may be difficult to assess on an individual customer basis, on a service level some contexts are more likely to attract customers with a need for social interaction (e.g., services that require advice, such as in travel agencies, financial services) than others (e.g., relatively standardized services, such as fast-food restaurants).

5.3 | Limitations and future research

In spite of the interesting results, this study has some limitations that may provide directions for further research. First, this study considered a limited number of robots to establish differences in their perceived human-likeness. The robots selected in the vignettes are the ones that are a good representation of their category. However, considering more (diverse) frontline robots in service interactions

may help identify other relevant design characteristics (Rosenthal-von der Püthen, & Kramer, 2014).

Second, this study has concentrated on the direct relationships between a robot’s humanness and customer’s value expectations. However, recent proposals suggest potential mediating mechanisms. For instance, psychological ownership reflects “the extent to which technology infusion provides customers with a sense of control in service experiences, an ability to understand and express their self-identity, and a sense of belongingness” (Van Doorn et al., 2017, p. 44). It may be interesting to evaluate whether this concept is equally important in parasocial interactions as in robot products (e.g. a home robot cleaner). Complementarily, future research could consider other robot features leading to a higher robotic social presence and humanness (cf., Van Doorn et al., 2017). In particular, scholars should pay attention to the concept of warmth when applied to a service robot. Further research is needed to clarify how to design robots with improved social skills that could enhance rather than harm customer experience (e.g., social support apps, Gelbrich et al., 2020).

Finally, this study has evaluated robots in one frontline setting but future research may consider frontline jobs involving different skills (e.g., mechanical or analytical skills [Huang & Rust, 2018]) to evaluate whether the relevance of human-likeness, competence and warmth differs across jobs or not. A robot’s human-likeness could be modified differently depending on the context. For instance, a recent study focused on chef robots found that customers’ perception of food quality was more positive when cooked by a robot with human-like hands compared to mechanic hands (Zhu & Chang, 2020). In this regard, the current study focuses on restaurants as a prototypical context in the hospitality sector that involves interactions between customers and frontline agents combining functional and social skills. Nevertheless, to assess the generalizability of the findings, the study should be replicated in other sectors in which frontline robots are employed for other kind of interactions (e.g., transaction based).

In sum, further research should continue advancing on customers’ perceptions towards service robots as social agents to better understand how to deal with this ongoing phenomenon from a marketing point of view.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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APPENDIX 1



K5



Savioke



Toro



Atlas



HRP-4



Robothespian



HRP-4C

Actroid
Geminoid

Kodomoroid



Han



Sophia



Asuna



Erika

APPENDIX 2

General introduction:

We would like to introduce Casey to you. Due to technological and economic circumstances, experts from several disciplines predict that many robots like Casey will be included in restaurants and similar customer-facing services soon.

As you see in the picture, Casey represents the latest innovation in robotics and has been specifically created to do waiter tasks. Consider a real and well-known mid-class restaurant in your city in which you have been dining several times before. Imagine that this restaurant has recently introduced one of this robots in its service, and that the next time you visit the establishment you might be served by Casey.

Description of the scenarios:

Low competence – Low Warmth

After one month at service, you are considering visiting the restaurant. To have some information in advance, you read a local newspaper's interview to a family served by Casey. Customers say "We have been served twice by the robot, but we think Casey is not particularly capable and organized. Robot mistakes occur too frequently, such as forgetting or switching orders. There have been a lot of complaints about Casey's mistakes. In addition, the robot is not particularly friendly or easygoing. When we asked for more ketchup, Casey replied in a serious and dry manner, using a monotonous tone."

A friend of you who recently visited the restaurant told you "It is true; the robot is not good at service. We asked about the Italian wines served at the restaurant, but Casey suggested a popular German Riesling. Also, the robot is rude when treating customers."

Low competence – High Warmth

After one month at service, you are considering visiting the restaurant. To have some information in advance, you read an interview in a local newspaper to a family served by Casey. Customers say "We have been served twice by the robot, but we think Casey is not particularly capable and organized. Robot mistakes occur too frequently, such as forgetting or switching orders. There have been a lot of complaints about Casey's mistakes. However, the robot is friendly and easygoing. When we asked for more ketchup, Casey replied with sympathy and respect.

Indeed, the robot made a joke about the ketchup and the food with very good sense of humor."

A friend of you who recently visited the restaurant also told you "It is true; the robot is not good at service. We asked about the Italian wines served at the restaurant, but Casey suggested a popular German Riesling. However, the robot treats customers with excellent good manners."

High competence – Low Warmth

After one month at service, you are considering visiting the restaurant. To have some information in advance, you read an interview in a local newspaper to a family served by Casey. Customers say "We have been served twice by the robot, and we think Casey is capable and organized. The robot served all the orders on time and perfectly as we demanded. However, the robot is not particularly friendly or easygoing. When we asked for more ketchup, Casey replied in a serious and dry manner, using a monotonous tone."

A friend of you who recently visited the restaurant told you "It is true; the robot is really good at service. We asked about the Italian wines served at the restaurant, and Casey suggested us three Italian wines with detailed information about their origins and tastes. However, the robot is rude when treating customers."

High competence – High Warmth

After one month at service, you are considering visiting the restaurant. To have some information in advance, you read an interview in a local newspaper to a family served by Casey. Customers say "We have been served twice by the robot, and we think Casey is capable and organized. The robot served all the orders on time and perfectly as we demanded. In addition, the robot is friendly and easygoing. When we asked for more ketchup, Casey replied with sympathy and respect. Indeed, the robot made a joke about the ketchup and the food with very good sense of humor."

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