THE SERVICE INDUSTRIES JOURNAL
2020, VOL. 40, NOS. 3–4, 203–225
https://doi.org/10.1080/02642069.2019.1672666

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

Service robot implementation: a theoretical framework and research agenda
服务机器人的使用： 理论架构及研究议程

Daniel Belanche [a], Luis V. Casaló [b], Carlos Flavián [a] and Jeroen Schepers [c]

[a]Faculty of Economy and Business, Universidad de Zaragoza, Zaragoza, Spain; [b]Faculty of Business and Public Management, Universidad de Zaragoza, Huesca, Spain; [c]Innovation, Technology Entrepreneurship & Marketing (ITEM) group, Eindhoven University of Technology, Eindhoven, The Netherlands

ABSTRACT

Service robots and artificial intelligence promise to increase productivity and reduce costs, prompting substantial growth in sales of service robots and research dedicated to understanding their implications. Nevertheless, marketing research on this phenomenon is scarce. To establish some fundamental insights related to this research domain, the current article seeks to complement research on robots' human-likeness with investigations of the factors that service managers must choose for the service robots implemented in their service setting. A three-part framework, comprised of robot design, customer features, and service encounter characteristics, specifies key factors within each category that need to be analyzed together to determine their optimal adaptation to different service components. Definitions and overlapping concepts are clarified, together with previous knowledge on each variable and research gaps that need to be solved. This framework and the final research questions provide a research agenda to guide scholars and help practitioners implement service robots successfully.

摘要

服务机器人和人工智能承诺可以提高生产力，降低成本，推动服务机器人的销售并推动那些致力于了解服务机器人应用研究的大幅增长。但是，有关于这一现象的市场营销的研究少之又少。本文旨在这一研究领域提供一些基本的观点，通过服务行业经理在服务环境中必须选择推行服务机器人的因素开展调查， 补充与人类相似的机器人方面的研究。由 机器人设计，客户特点以及服务接触特点三个部分所组成的架构，明确指出其构成的主要因素， 这些主要因素分布在每一个需要通过分析来决定其在不同服务组成部分的最佳应用的类别之中。本文在之前文献的基础上阐明了每一个变量重复的概念以及需要解决的研究空白。 本理论架构及最终的研究问题为学者们提供了一个研究议程， 并且帮助从业者成功的使用服务机器人。

ARTICLE HISTORY
Received 20 August 2019
Accepted 22 September 2019

KEYWORDS
Service robots; artificial intelligence; framework; human-likeness; anthropomorphism; robot design; customer features; service encounter characteristics

关键词
服务机器人; 人工智能; 架构; 与人类相似; 拟人化; 机器人设计; 客户特点; 服务接触特点

CONTACT Jeroen Schepers J.J.L.Schepers@tue.nl
This article has been republished with minor changes. These changes do not impact the academic content of the article.

© 2019 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group
This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (http://creativecommons.org/licenses/by-nc-nd/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way.

1. Introduction

The rise of robots, a decades-long process throughout many sectors, has finally reached service industries. Advanced robotics, artificial intelligence (AI), and machine learning technology enable providers to offer their services with greater productivity, efficacy, and efficiency (Wirtz et al., 2018). A survey to business leaders reveal that 24% of US companies are already using AI, and a 60% expect to use it by 2022 (Genesys, 2019). From the customer domain, 62% of users of voice-based digital assistants (e.g. Siri, Alexa) plan to buy something through these smart devices within the next month (GoGulf, 2018). Sales of service robots continue growing, at annual rates of greater than 30%, and the International Federation of Robotics (2018) anticipates even greater expansions in the use of service robots for professional and personal purposes in the next decade. Robots introduced to perform public interactions are gaining particular prominence (see Figure 1). For example, Pepper, a mass-produced, sociable humanoid robot currently in use by more than 2000 companies, can welcome, inform, and guide visitors. Its 'little brother' Nao has sold more than 13,000 units worldwide (SoftBank Robotics, 2019), and the context-specific LoweBot answers customers' questions in Lowe's stores (Rafaeli et al., 2017).

The social, economic, and labor consequences of this spread of robots are thus pertinent questions. In particular, automated agents increasingly will replace human employees, even in complex, analytical, intuitive, and empathetic tasks (Huang & Rust, 2018). Some recent, small-scale empirical studies address consumers' psychological reactions to robot aesthetics (e.g. human-likeness), which might affect people's comfort during service robot interactions (Mende, Scott, van Doorn, Grewal, & Shanks, 2019; Van Pinxteren, Wetzels, Rüger, Pluymaekers, & Wetzels, 2019). Yet marketing studies of service robots remain scarce, and just a few theoretical works consider the distinctive features of related technologies and their global implications (Huang & Rust, 2018; Wirtz et al., 2018). Nor have previous consumer behavior articles investigated robot design factors that might need to be adapted, according to distinctive characteristics of service customers and service situations. More importantly, we know of no existing frameworks

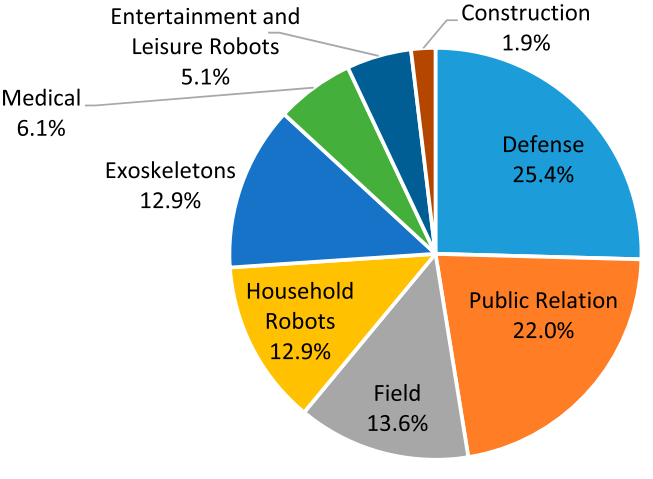


Figure 1. Sectors of global sales of service robots in 2017 (excluding logistics). Source: International Federation of Robotics (2018).

designed specifically to help researchers set up meaningful conceptual frameworks for their study and at the same time help practitioners increase the likelihood of a successful introduction of service robots. In this sense, even the scant available literature on service robots has ignored crucial questions that service managers must answer when implementing service robot in their companies.

With this study, we seek to bring more structure to a topic of emerging relevance by outlining a framework for future studies and decisions on robots in the frontline of organizations. We start by reviewing previous literature to identify key concepts and origins and thereby establish a foundation for understanding fundamental features of service robots. In so doing, we discover that the complexity of the topic requires considerations of not just robot design aspects but also the integration of customer features and service encounter characteristics. We illustrate this three-part framework by providing actual examples of AI and robotic agents currently at service, and explaining the existing research knowledge, often insufficient, related to each aspect. From this research framework, we also derive an agenda for further services marketing research that explicitly accounts for practitioners' demand for practical implications. Specifically, service managers must make complex choices within each category (robot design, customer features, and service encounter characteristics) in our three-part framework when introducing robots into their specific service contexts. Thus, we contribute to extend previous knowledge focused on customer's willingness to use service robots (e.g. Lu, Cai, & Gursoy, 2019) by addressing the managerial decisions regarding this service innovation from a practical approach. Finally, we reveal some continued research gaps that researchers might address in novel research that can specify the determinants and moderators of the successful introduction of service robots. In sum, our research contributes to organize previous knowledge on the emerging phenomenon of service robots around a useful framework indicating the key factors to be researched by scholars in order to help practitioners succeed in the implementation of service robots.

2. Service robots: concepts and definitions

Because of the nascent status of this research domain, defining the terms used to describe similar concepts is a critical and necessary effort, to establish the limits of the field and which approaches are most relevant. In particular, *robot* is a standardized, general term, though several overlapping concepts also can describe robotic entities. Derived from the Czech word *robota*, which means 'forced labor' or 'slavery' (Capek, 1920), robot also can describe mechanical devices programed to perform specific physical tasks. It implies some level of autonomous action, without human intervention (International Federation of Robotics, 2016), though this level of autonomy varies widely, from a robotic arm performing a repetitive manufacturing task to the Curiosity robot that has been exploring Mars for more than six years.

To describe their physical appearances, terms such as humanoid or android are common, often used indiscriminately, to refer to robots with anthropomorphic figures (Van Doorn et al., 2017), though the terms also imply the tasks that robots can perform. Walters, Syrdal, Dautenhahn, Te Boekhorst, and Koay (2008, p. 164) propose three categories, according to the level of anthropomorphism (Gong & Nass, 2007; MacDorman & Ishiguro, 2006): (1) mechanoids, which are relatively machine-like in appearance with no overtly human-like features; (2) humanoids that are 'not realistically human-like in appearance and readily perceived as

robot by human interactants … [but] possess some human-like features, which are usually stylized, simplified or cartoon-like versions of the human equivalents, including some or all of the following: a head, facial features, eyes, ears, eyebrows, arms, hands, legs'; and (3) droids (android if male, gynoid if female), whose 'appearance and behavior … is as close to a real human appearance as technically possible,' designed to be perceived as fully human. A drone refers to an unmanned, aerial vehicle (Goodchild & Toy, 2018).

Artificial intelligence (AI) pertains specifically to 'machines that exhibit aspects of human intelligence' (Huang & Rust, 2018, p. 155). An early prediction from the Dartmouth Conference of 1956 proposed that 'every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it' (McCarthy, Minsky, Rochester, & Shannon, 2006, p. 13). Focused on the technological capacity to perform tasks, rather than physical skills or appearance, AI initially was envisioned as a way to combine perception, reasoning, and actuation. Over time though, AI development has focused more on algorithms (virtual), while robotics has addressed mechanical functioning (physical) (Rajan & Saffiotti, 2017). From a service management perspective, the value of AI stems not from its virtual or unrecognized use but rather on the technology's ability to engage with customers at a social level (Van Doorn et al., 2017). Because of its lack of a bodily manifestation, AI generally involves text- or voice-driven conversational agents, such as chatbots and voice-based assistants (De Keyser, Köcher, Alkire, Verbeeck, & Kandampully, 2019). In social media settings, bots or social bots can refer to software-based robots that explicitly generate text to create a kind of artificial buzz, often to manipulate or deceive social media users (Ferrara, Varol, Davis, Menczer, & Flammini, 2016).

For services, robotics and AI need to be integrated (Rajan & Saffiotti, 2017). The International Federation of Robotics (2016) defines service robots as those 'that perform useful tasks for humans or equipment excluding industrial automation applications.' Focusing on frontline operations, Wirtz et al. (2018, p. 909) define them as 'system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers.' For this article, we use service robots as a general term to refer to the autonomous technology employed in frontline operations with some physical interface; still, most of our discussion also applies to other actions performed by different entities in a service domain.

3. Toward a new framework for a new field of research

As this definitional effort indicates, robots are technological entities with some human features, either real or simulated. In service settings, previously inhabited by either machines or employees, a service robot represents something in between, with technological features but also the ability to engage in human interactions. Therefore, service robots constitute a novel field of research, due to their distinctive, disruptive features. They can engage customers on a social level (Van Doorn et al., 2017), so that unlike interactions with self-service technologies, customers perceive that they are interacting with another social entity that is providing services. Such perceptions vary with customers' features too. Service robots also operate autonomously, directed by AI without needing instruction or human help (Colby & Parasuraman, 2016), unlike technologies that require employees' or customers' effort. This feature creates new interaction possibilities, depending on the service encounter characteristics, such as varying the contributions by the robot (e.g.

management of investments by a robo-advisor in financial services settings). Because service robots combine advanced forms of intelligence (mechanical, analytical; Huang & Rust, 2018), they also can perform complex tasks that previously required human intelligence (Tussyadiah & Park, 2018).

Considering these unique features, we need to integrate the robot's design features, such as whether it can respond to social cues, with customers' own features and perceptions and with service encounter characteristics that inform the structure and success of a service provision episode. Therefore, rather than focusing on the effect of a single variable on service performance, we propose that researchers structure their work along a three-part framework in which the interaction across the three factors is inherent and requires simultaneous analyses. Figure 2 depicts our proposed framework; the combination of the choices in each of the three parts, or dimensions, determines the performance of service robots, in terms of acceptance, customer satisfaction, and loyalty to the service provider. The challenge is finding the optimal combination. For example, a younger customer (customer features) with questions about a banking service (service encounter characteristics) may prefer informal interactions with a chatbot (robot design).

4. Robot designs

We start with the complexities associated with robot designs, which should seek to enhance customer–service provider relationships. Previous literature on robotics has mostly focused on aesthetics and physical appearances and how they influence human perceptions and attitudes toward robots. However, there are much more choices to be made with regard to robot design. We therefore consider these elements to establish six key factors of service robot design, as summarized in Figure 3.

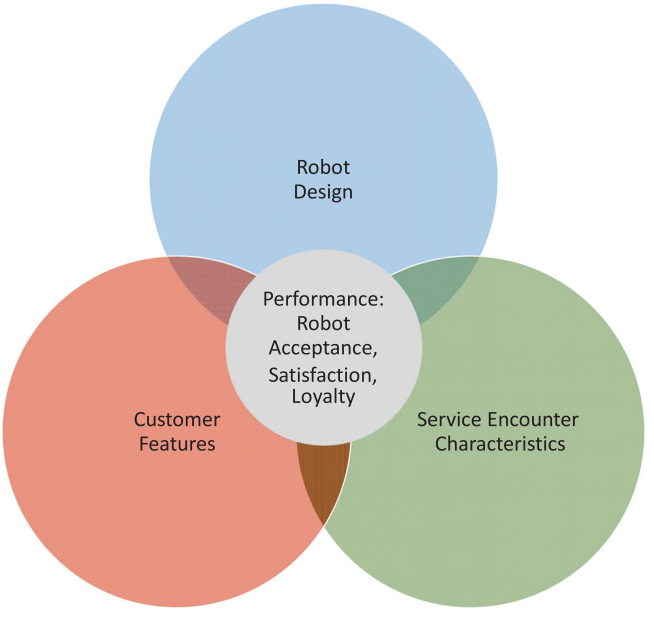


Figure 2. Three-part framework for service robots.

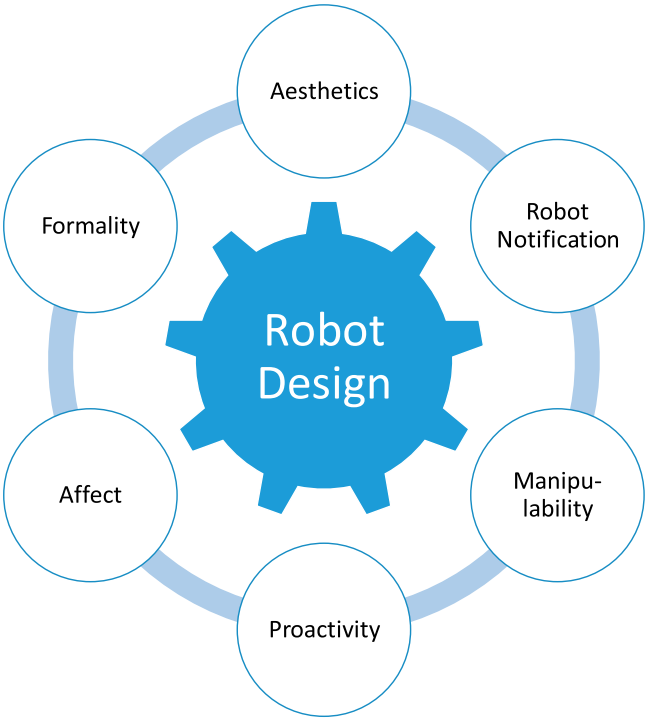


Figure 3. Key factors of service robot design.

4.1. Aesthetics

As indicated above, previous literature on robotics has mostly focused on aesthetics and physical appearances, often with an assumption of a positive correlation between robot human-likeness and users' acceptance (Walters et al., 2008). However, the optimal level of human-likeness (Tinwell, Grimshaw, & Williams, 2011b) has not been established clearly (Burleigh, Schoenherr, & Lacroix, 2013; Rosenthal-von der Püthen & Kramer, 2014), suggesting the moderating effects of customer features or encounter characteristics, as we address subsequently (Van Pinxteren et al., 2019). In a general sense, higher levels of human appearance seem to amplify emotional attachment, induce positive perceptions and attitudes, and increase trust in and preference for robots (Tussyadiah & Park, 2018; Van Pinxteren et al., 2019). This positive effect likely arises because a human appearance of a technological object increases customers' access to a human schema, due to the human-like congruency (e.g. Aggarwal & McGill, 2007).

However, understanding the link between human-likeness and favorability also might depend on the uncanny valley effect (Mori, 1970), which predicts that people's affinity toward robots increases with greater human-likeness, so robots that look somewhat like humans evoke greater affinity, but beyond some point, their human-likeness becomes unpleasant, eerie, or creepy. This widely debated assertion (Walters et al., 2008) has been criticized for ignoring people's affinity with robots (i.e. familiarity, affect, reversed eeriness), as well as the likely causes of any such effect (see Rosenthal-von der Püthen & Kramer, 2014). Empirical research also does not offer conclusive support for the uncanny valley effect (Burleigh et al., 2013), so some researchers claim acceptance

always increases together with the level of human-likeness (Rosenthal-von der Püthen & Kramer, 2014; Tinwell et al., 2011b). For services marketing, robots also may require social presence (Heerink, Kröse, Evers, & Wielinga, 2010), defined as 'the extent to which machines (e.g. robots) make consumer feel that they are in the company of another social entity' (Van Doorn et al., 2017, p. 44). The similar concept of perceived humanness (Wirtz et al., 2018) reflects robots' capacity to be almost indistinguishable. Finally, robot anthropomorphism represents a widely researched factor.

The level of human-likeness or robot anthropomorphism also is crucial to customer acceptance, together with robots' apparent or implied gender, ethnicity, and culture. Other technical design aspects, such as material and size, might be relevant too, especially to avoid any sense of physical risk among consumers (Takayama & Pantofaru, 2009). Chatbots might evoke anthropomorphism through the use of human instead of robotic names (e.g. Emma vs. ChatBotX) or claims of human-like skills (Araujo, 2018). The inclusion of pictures also might define chatbot features (e.g. human picture, avatar picture to suggest a chatbot's identity in terms of age or gender).

4.1.1. Anthropomorphism

Consumers often attribute human characteristics to nonhuman entities (Epley, Waytz, & Cacioppo, 2007); brand and product designers seek to encourage such anthropomorphism by adding human features, such as the shape of a face or a smile, to encourage consumer familiarity, engagement, and positive evaluations (Lu et al., 2019; Mourey, Olson, & Yoon, 2017). When robots adopt human-like appearances, it can facilitate human–robot interactions and encourage the application of established social norms. Previous robot design studies note that an appearance that evokes greater perceptions of human-likeness also lead to a stronger sense of social presence (Kim, Park, & Sundar, 2013) and social inclusion (Mourey et al., 2017). Customers prefer to spend more time with robots presenting higher levels of anthropomorphism or perceived intelligence (Qiu, Li, Shu, & Bai, 2019). Crucial human-like features include a head (Yu & Ngan, 2019) and facial expressions of emotions or intentions (Takanishi, 2000), especially during face-to-face interactions (Kiesler, Powers, Fussell, & Torrey, 2008).

4.1.2. Gender

Designing human-like robots without any signal of gender can be challenging and introduce other biases. For example, spoken responses by AI or chatbots might use a male, female, or neutral voice; any of these choices likely affects customers' reactions. Thus, questions about robots' gender are gaining attention (Alesich & Rigby, 2017; Stroessner & Benitez, 2019). Many companies tend to use feminine features (Siri, Alexa), seemingly with the assumption that female robots evoke more positive evaluations, greater trust, and more desire for contact than male robots (Stroessner & Benitez, 2019).

4.1.3. Ethnicity and culture

Issues surrounding of robot ethnicity and culture have prompted less research interest thus far (Makatchev, Simmons, Sakr, & Ziadee, 2013). Robots frequently exhibit conventionally Asian features, likely because many of the firms developing robots are Japanese (MacDorman, Vasudevan, & Ho, 2009). In this respect, robots might reflect the ethnic features of their originators, signaling a match between the robot and the designer, as well as

its firm or brand origin. To adapt these products to different cultures though, robots might need to exhibit varying ethnic features, in line with the prediction that customers sense a closer connection to robots that appear to belong to the same cultural group (Obaid et al., 2016). That is, humans likely apply social categorization rules to robots and exhibit in-group favorability (Eyssel & Kuchenbrandt, 2012; Makatchev et al., 2013). Yet robots whose appearance is representative of different ethnicities or cultures also might be introduced to signal the cultural diversity of the brand or firm. Another issue, for voice-based AI and chatbots, is whether the voice used should be accented or not, as well as how to ensure every robot is fully fluent and natural sounding in various languages (Yu, 2019).

4.2. Robot notification

Another critical decision in designing a service robot is whether customers should know that they are interacting with a robot, because robot notification makes it clear to them. Although this decision is especially important in robots whose mechanics are not visible to customers (e.g. chatbots), robots' appearance becomes increasingly natural and may be indistinguishable from a human in future. The awareness among customers of interacting with a robot determines their expectations of the interaction. The Turing test is a classic challenge; it asks whether robots can become so good at interacting with a human that the human cannot confirm that he or she is interacting with a robot. Several robotic conversational agents have passed this Turing test; a chatbot named Eugene Goostman was the first to do so in 2014 (Shah, Warwick, Vallverdú, & Wu, 2016). If humans cannot conclusively determine that they are talking to a machine, they are less aware of an artificial interlocutor in a service context. Customer awareness may involve several levels (social, task, job awareness) that can evoke different inferences, thoughts, and reactions (Drury, Scholtz, & Yanco, 2003). To avoid negative consequences, service companies must consider various possibilities: notify the customer upfront ('you are now going to chat with Alice, our service robot'), afterward ('this chat was hosted by Alice'), or not at all. Several organizations are engaged in a race to design an indistinguishable robot with a nearly perfect human look; the robot Sophia is the first automated agent to have received citizenship in a country (Pagallo, 2018).

4.3. Manipulability

The service experience might be customized by consumers, according to their personal preferences or the type of contact (Van Doorn et al., 2017). Customers differ in their control perceptions relative to service robots, such as cars, heaters, and lawn mowers (Jörling, Böhm, & Paluch, 2019). Greater robot manipulability implies a stronger value co-creation role for customers (Jussila, Tarkiainen, Sarstedt, & Hair, 2015). Manipulability also relates closely to the concept of psychological ownership, which stems from a sense of control or ownership due to the presence of an extended self (Belk, 2013; Pierce, Kostova, & Dirks, 2001). The level of manipulability also could have important implications for responsibility following a negative outcome (Jörling et al., 2019). To increase or decrease manipulability, companies can design customers' physical interactions with robots, such as talking, moving, touching the robot, or pushing buttons on a display. Some features might be added to reflect the focal task, such that caregiving robots, taking the form of a pet or toy (e.g. cat, seal; Broadbent,

Stafford, & MacDonald, 2009), feature a soft surface to encourage touch and caressing. Such interactions can enhance the sense of connection between, for example, an elderly patient and a caregiving robot designed to look like a cat that also tracks the person's movement (e.g. to prevent falls) and offers reminders (e.g. to take medication) (Wada & Shibata, 2007). Even when robots intentionally are designed not to look human, their features can facilitate social connections and uses; a driverless car does not need to look human but rather should be similar in appearance and function to other vehicles, so that human users sense that they can manipulate it as they would a conventional car, and thus feel more trust in the technology (Choi & Ji, 2015). Similarly, autonomous robot vacuum cleaners give customers an easy means to stop them or design their routes (e.g. blocking off stairs) as needed (Vaussard et al., 2014).

4.4. Proactivity

In human–robot interactions, proactive service behavior occurs when the robot initiates the encounter or provides anticipatory helping (Grant, Parker, & Collins, 2009). A proactive frontline service robot might initiate the flow of communication, offer assistance, or seek out opportunities to help customers, rather than just responding to requests (Rioux & Penner, 2001). Garrell, Villamizar, Moreno-Noguer, and Sanfeliu (2017) note that human users teach the Tibi robot to be more proactive. For human frontline employees, proactivity can prompt positive service outcomes, but so can a more reactive style (e.g. Bitner, Booms, & Tetreault, 1990). Customer reactions to a proactive robot could mimic those to proactive human employees, but they likely differ in several ways too, especially when we consider the complementary influences of flow in a human–robot interaction. In reacting to customer stimuli, robots likely differ from human frontline employees in terms of the amount of information they offer and their response time. Waiting for a response may prompt positive or negative customer perceptions and satisfaction levels (Giebelhausen, Robinson, & Cronin, 2011).

4.5. Affect

The incorporation of emotions in robotic agents is among the most challenging design issues facing designers today, and success appears several decades away (Huang & Rust, 2018; Lim & Okuno, 2015). Replicating the visual and auditory cues that mark virtually any human employee–customer encounter would be difficult, requiring consideration of the body, movements, voice, and mental states (e.g. mood, emotional state) (Cha, Kim, Fong, & Mataric, 2018). In particular, empathy is essential to employee–customer service encounters (Wieseke, Geigenmüller, & Kraus, 2012), but it represents an extremely high level of service robot affective achievement (Huang & Rust, 2018). Still, AI technology already fulfills with some of the four branches of emotional intelligence (i.e. perceiving, assimilating, understanding and managing emotions, Prentice, Dominique Lopes, & Wang, 2019). AI enables robots to identify human emotions (e.g. face tracking; Canal, Escalera, & Angulo, 2016) and pretend to have feelings (Lim & Okuno, 2015). What is more, humans are good at interpreting robot gestures and behaviors as affective cues (Gácsi et al., 2016). Service robots with a physical appearance express feelings, using precise face and body language (Thimmesch-Gill, Harder, & Koutstaal, 2017). Chatbots also can use emoticons as a 'universal language' to express emotions, and this domain holds great research potential (Fadhil, Schiavo, Wang,

& Yilma, 2018). Furthermore, virtual assistants can leverage voice tones to express affect (Ghosh & Pherwani, 2015), whereas traditional nonverbal signaling methods (e.g. beep, chirp; Cha et al., 2018) might be reserved for basic functions (e.g. switch on/off). However, unanimated forms of facial expressions or that diverge from the human norm (i.e. inability to communicate emotions) could increase perceptions of uncanniness or negative emotions such as fear and unsafety (Tinwell, Grimshaw, Nabi, & Williams, 2011a; Yu, 2019). Uncanniness might stem from people's attributions of robots' capacity to feel and sense (Brink, Gray, & Wellman, 2019) or negative perceptions related to category conflict (machine vs. human) (Burleigh et al., 2013). In this sense, greater levels of human-likeness might increase consumer discomfort, leading them to display compensatory responses (e.g. purchasing status goods, seeking social affiliation, eating more; Mende et al., 2019).

4.6. Formality

The level of formality in the customer–robot interaction varies by design as well. In formal interactions, an agent adheres to normative prescriptions and firm policies; in informal interactions, idiosyncrasy and prerogative (e.g. use of casual language) dominate (Marlow, Taylor, & Thompson, 2010). Robots can be designed in a wide range of communication styles, ranging from highly formal to highly informal (Shamekhi, Czerwinski, Mark, Novotny, & Bennett, 2016). In research with a kitchen assistant robot, people express surprise when the robot uses informal expressions, leading to doubt and negative affective reactions (Torrey, Fussell, & Kiesler, 2013). Robots designed to amuse people, such as CleverBot, might respond to messages with jokes, wit, or memes. Robots' sense of humor at Marriott hotels is based on specific expressions (e.g. 'I am just chilling, please remove your [cold] drinks', Lu et al., 2019). This signal of the robot's personality and warmth thus can vary the formality of the interaction (Tay, Jung, & Park, 2014), and the kind of communication style might be either standardized or adapted to customer traits and preferences, leading to different reactions (as we discuss in the next section). If robots rely on physical features that are dissimilar to human ones (e.g. wheels instead of legs), they also can be useful for performing mechanical tasks (i.e. industrial robots) and formal, sophisticated jobs that require high degrees of precision, such as surgery (Liu, Xiong, He, Chen, & Huang, 2018).

5. Customer features

Disruptive innovations, such as service robots, are perceived and welcomed in various ways by different customers, according to their capacity to deal with the innovation or disruption. Many consumers feel awe or fear in the face of a novel, disruptive technology (Belk, Humayun, & Gopaldas, 2019), but as robots increasingly function as social agents in service settings, providing both technology advances and some level of humanness, this link grows more complex. Figure 4 depicts key customer features to consider when introducing service robots.

5.1. Technology readiness

Some people exhibit a propensity to embrace new technologies to accomplish daily tasks (Parasuraman, 2000). Technology-based services thus can trigger positive or negative

feelings (Mick & Fournier, 1998), depending on people's level of technology readiness, comfort, and use (Parasuraman, 2000). Technology readiness also depends on people's optimism, innovativeness, discomfort, and insecurity in response to a technology (Parasuraman & Colby, 2015). For robots with more advanced functions, such as the Beam Smart Presence System, which moves around and monitors the house when people are not at home, customers with higher technology readiness are appropriate target markets. As far as service robots represent a disruptive technology, customers' technology readiness, in combination with key design factors, likely determine whether they embrace their use. Groups of customers, defined by their levels of technology readiness, could be useful for beta testing or segmentation purposes.

5.2. Age

Older people generally have more negative attitudes toward robots and technology (Hudson, Orviska, & Hunady, 2017; Onorato, 2018). Before they will accept service robots, they may require certain design features (e.g. less proactivity, more formality). For example, older people express reluctance to interact with robot nurses who replace human health care providers and eliminate a sense of touch; they also prefer even video assistance by a human caregiver (Song, Wu, Ni, Li, & Qin, 2016). The absence of human-like features can reduce their expectations though, as we noted previously (Broadbent et al., 2009), such that many elderly care robots are designed to look like an animal or cuddly toy. The context also is crucial here; the use of assistive robots in elder care is

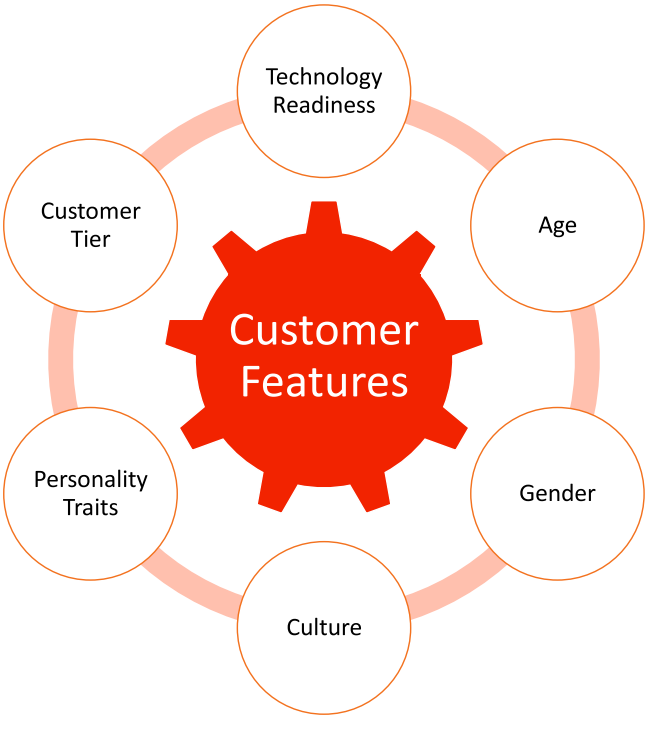


Figure 4. Key customer features for service robots.

growing but also could lead to value creation or destruction (Čaić, Odekerken-Schröder, & Mahr, 2018), and it has sparked some new controversies (Hudson et al., 2017). In contrast, younger customers tend to accept robots as a tool to accomplish simple, repetitive tasks in service sectors, such as tourism (Ivanov, Webster, & Garenko, 2018). Assistive robots also can help children perform specific tasks related to health care and rehabilitation (Pulido et al., 2017), as well as in the education sector, evoking better results among primary rather than in secondary school students (Fernandez-Llamas, Conde, Rodríguez-Lera, Rodríguez-Sedano, & García, 2018). Thus, children might be a particularly indicated segment to embrace service robots.

5.3. Gender

In reaction to most technologies, woman tend to express more negative perceptions than men (Chen & Huang, 2016). Mothers are more reluctant than fathers to rely on educational robots for their children (Lin, Liu, & Huang, 2012), though the research that uncovers this effect does not address any moderating or mediating factors. Customer gender has been studied frequently as a moderating variable, but further research needs to specify situations in which gender is relevant for service robot acceptance. When service robots function as social agents, interaction possibilities also expand across sectors; some preliminary research suggests that matching robot and customer genders can increase comfort levels (Carpenter et al., 2009).

5.4. Culture

Attitudes toward robots are shaped by culture (Bartneck, Suzuki, Kanda, & Nomura, 2007; Belanche, Casaló, & Flavián, 2019). Some evidence suggests Japanese customers are more prone to accept robots (MacDorman et al., 2009), and this trend might extend to other Asian cultures (Rau, Li, & Li, 2009). Yet this proneness also might reflect a cultural stereotype; other countries might indicate even more positive attitudes (Bartneck et al., 2007). Design factors, such as the level of anthropomorphism and manipulability, likely moderate any cultural influences (Bartneck et al., 2007). Overall, further research should undertake cross-cultural analyses to determine the outcomes of variations in cultural dimensions (e.g. Hofstede, n.d.); individualism may lead to positive attitudes, whereas uncertainty avoidance could lead to negative attitudes, for example. Studying culture in combination with robot design and service contact features could help increase acceptance in specific service settings.

5.5. Personality traits

Individual personality traits similarly may be crucial for establishing people's attitudes toward service robots (Woods et al., 2007). According to Person–Environment Fit Theory, extroverted people should feel more comfortable and satisfied when interacting with similar agents in a service encounter (Babakus, Yavas, & Ashill, 2010); they may prefer to interact with more informal or proactive service robots. Previous research already indicates that extroverted people interact more smoothly with automated agents (Chen, Tseng, Lee, & Yang, 2011). Other personality traits (e.g. openness, conscientiousness, agreeableness, neuroticism; Goldberg, 1990) also might exert influences. In line

with these likely moderating effects, companies might look to match customer personalities with robot designs, in terms of robot formality (Woods et al., 2007) or human aesthetics (e.g. introverts prefer mechanical-looking robots; Walters et al., 2008).

5.6. Customer tier

A customer orientation might be supported by effective designs of robot technologies and thus generate customer lifetime value (Moon, Miller, & Kim, 2013). Yet we know little about the effect of different customer tiers with regard to service robot acceptance. Very loyal customers arguably might feel insulted if the firm assigns a robot rather than an employee to help them. From a cost perspective, relying on a robot to help a potential or new customer might be very efficient in terms of acquisition cost and acclimate this new buyer to such interactions. Companies' communication strategies (Zhang, Liang, & Wang, 2016) and customers' attributions of the innovation (e.g. service enhancement versus cost cutting, Nijssen, Schepers, & Belanche, 2016) likely moderate this influence.

6. Service encounter characteristics

At service 'moments of truth,' frontline rapport may differ greatly, depending on the kind of service and how well the service robot adapts to the service encounter characteristics, as detailed in Figure 5. For example, robots that are not designed to interact with humans might not need any human aesthetic properties, but if they are going to appear in any space that might be shared with human employees or customers, they need to exhibit appropriate levels of basic factors, such as size, speed, or security (Liu et al., 2018). That is, even if they lack specific human features, service robot characteristics must reflect normative standards to become integrated into a social world. For example, excessive height and velocity exhibited by basic robots increase people's sense of threat and anxiety, even if they do not interact (Hiroi & Ito, 2009). Such considerations grow even more critical in service encounters in which humans are accustomed to interacting according to basic social norms.

6.1. Information provision

Robots can be helpful at different stages of the customer journey, such as providing information before purchase and guiding customers during it (Larivière et al., 2017). Providing information and advice is probably the simplest and most common task performed by service robots, as exemplified by the many companies that use chatbots or other AI-based online virtual assistants to help customers who access their websites or call centers. Robots also appear in brick-and-mortar settings; the Nao robot answers bank customers' queries in Tokyo (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017), and Connie robotic concierge addresses Hilton guests' needs of general information (Gursoy, Chi, Lu, & Nunkoo, 2019). Such autonomous agents tend to combine conversational abilities with other nonverbal communication features to facilitate information exchanges (Aaltonen, Arvola, Heikkilä, & Lammi, 2017). More research is needed to clarify customers' reactions to a robot in initial or prepurchase stages of their customer journey; their reactions likely vary, depending on the kind of service and their own customer features (e.g. new vs. loyal customers).

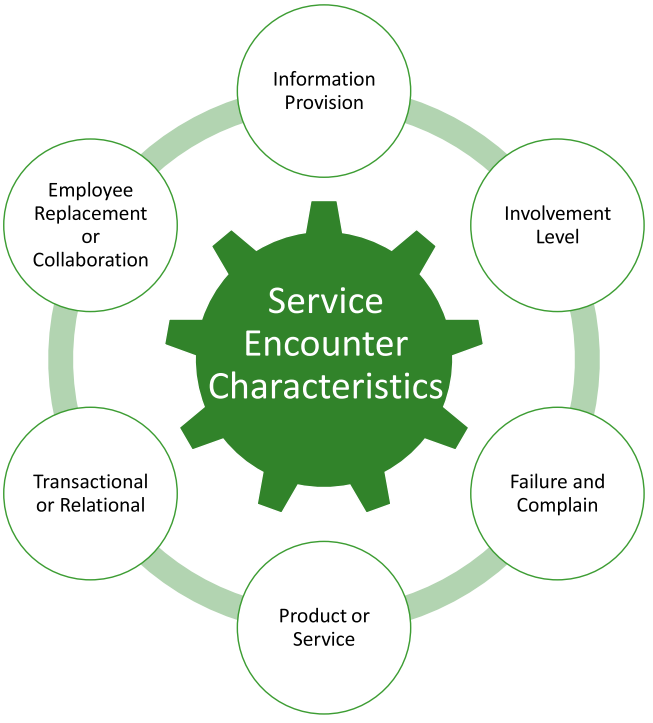


Figure 5. Key factors of service encounter characteristics for service robots.

6.2. Involvement level

Customers' level of involvement affects their information processing and decision making (Dholakia, 2001). Becoming involved in a new service development increases its personal relevance (Floh & Treiblmaier, 2006). Before secondary appraisal and outcome assessment, consumers first evaluate the relevance of AI to themselves (Gursoy et al., 2019). Depending on this relevance, as well as the complexity of the service, customers might express heightened levels of care about making the right choice among different service options. Thus, customer involvement strongly determines service robot acceptance, as far as it is related to customer motivations and risk perceptions (Dholakia, 2001). Investing a small amount in a fund managed by a financial robo-advisor may seem like a game, but customers instead might reject a robo-advisor when they invest vast sums or to obtain a mortgage (Belanche et al., 2019). In a complementary sense, customer involvement could be increased by situational engagement induced by interacting with a robot, such as when customers enjoy the novel experience of interacting with a robot agent for the first time (Aaltonen et al., 2017).

6.3. Failure and complaints

Customers are especially sensitive to the service provided following a failure (Brymer, 1991), and substantial literature confirms that a courteous, affective service recovery response improves customers' attitudes toward the company (Johnston & Fern, 1999). Employees' autonomy and flexibility after a service failure increase customers' satisfaction and loyalty

(Brymer, 1991). Thus, even if robots are useful in initial stages of the customer journey, they might be less suitable resolution agents in response to customers' complaints. This gap relates to robots' lack of comprehensive human abilities, including affective and empathetic perceptions, which are crucial to service recovery. However, increasing robot humanness, through anthropomorphism, reduces customers' dissatisfaction after a service failure (Fan, Wu, Miao, & Mattila, 2019). For the failure itself, robots might be designed to perform faultlessly, but they still can fail in a particular service provision encounter (Wirtz et al., 2018), and the implications of such a scenario demand further research.

6.4. Product or service context

Service provision can involve sales of both products and services, so decisions about how to introduce robots should address these differences. Frontline employees' skills and organizational routines appear more relevant and complex for service compared with product offerings (Nijssen, Hillebrand, Vermeulen, & Kemp, 2006). For example, it is relatively easy for an autonomous agent, such as an AI-driven online browser, to categorize and compare product information and provide it to customers. However, more sophisticated, specific skills are needed to provide customized service, reflecting the customer's needs and demands (Marinova et al., 2017). Some robots may be particularly competent in performing specific service tasks (e.g. surgery); regular, frontline interactions instead would require them to incorporate a wide range of multifaceted skills, including communication and emotional abilities.

6.5. Transactional or relational interactions

Even as marketing adopts a stronger relational focus, many companies continue to exhibit a transactional business orientation, instead of working to establish long-lasting customer–provider relationships (Sharma & Pillai, 2003). Customers differ in their relational orientations too: People with an exchange orientation expect benefits to overcome costs, whereas those with a communal orientation require service providers to behave responsibly (Van Doorn et al., 2017). Automation is particularly well suited to repetitive, simple tasks, so service robots may be especially useful in transaction-oriented service settings, as it could be the case of check-in tasks in hotels and airports (Lu et al., 2019). Research pertaining to caregiving services suggests that clients may develop relationships with robots (Broadbent et al., 2009), whereas in a more commercial setting (e.g. financial services), robots might be hard pressed to enhance the relational nature of the service encounter. Alternative robot designs for transactional services might be very useful; according to its developers, the proactivity of the Pepper robot helps increase its visibility and attract customers' attention, so Pepper actively seeks people to start conversations and stimulate their purchases (SoftBank Robotics, 2019).

6.6. Employee replacement or collaboration outcomes

The level of automated social presence also might alter the level of human social presence (Van Doorn et al., 2017). That is, technology may be substituting for frontline employees or complementing their efforts to facilitate the encounter. Some customers

engage directly with technology; others might interact with an employee who is being assisted by technology, running backstage (De Keyser et al., 2019). Even if the service outcome of both interactions is similar, customers likely behave differently, depending on their perceptions of the interacting agent, robotic or human. Employees-AI collaboration help build customer-employee rapport (Qiu et al., 2019); though, recent evidence in hospitality found that AI harms the productivity of emotional intelligent employees (Prentice et al., 2019). Huang and Rust (2018) suggest that companies thus must offer dual service provision: Some segments of customers will be willing to pay a premium for human interactions and human touch, and others will prefer basic services provided by autonomous systems.

7. Concluding remarks

This article seeks to bring attention to a topic of growing relevance and provide a framework to guide and stimulate further research into the expanding introductions of service robots. Each component in the proposed framework sparks research questions, and together, these questions constitute a viable research agenda, as we list in Table 1. This research contributes to review and organize previous knowledge in order to help researchers and practitioners address the key elements affecting a satisfactory introduction of service robots. Although it is beyond the scope of our proposed framework to offer a holistic model of all potential determinants of the success of a service robot implementation effort, we identify some essential factors, with clear managerial implications. In particular, recent research suggests that the elements of our framework influence service performance, customer satisfaction, customer-robot and customer-employee rapport building, and employees retention, among other important management indicators (Fan et al., 2019; Prentice et al., 2019; Qiu et al., 2019). By using the definitions and references we have offered to develop our framework, researchers can continue to investigate each element in greater depth, as variables in unique research projects. Scholars' research should help managers decide which combination of robot design, customer features and service design characteristics leads to a better implementation of service robots in their context. These researchers must acknowledge that many of these elements, such as human-likeness, are far more complex than previously described.

Moreover, we chose to exclude some technological advances that might be relevant for service robots in the future, because they currently remain inapplicable to service contexts. For example, exoskeletons eventually might integrate directly with individual users, and cyborg employees could raise new customer concerns (Belk et al., 2019).

Finally, our framework does not address ethical issues, which service managers must consider when implementing service robots. Some ethical concerns reflect the service sector specifically, such as military or sexual uses of robots (Belk et al., 2019). Subtler moral decisions also need to be considered in relation to the factors in our frameworks, such as design questions. Mixing robot and human features creates a new category, implying the need for further research not just from a marketing perspective but from ethical and sociological views. Stereotypes represent a key consideration, as indicated by evidence that customers accept robots more when they reflect occupational role stereotypes (e.g. female robots more accepted in healthcare; male robots more accepted in security;

Table 1. Potential research questions to establish a research agenda for service robots.

Framework path and subtopic	Research question
Robot design	
Aesthetics	To what extent should service robots feature anthropomorphic cues?
	Is there an optimal level of robot human-likeness?
	Should robots be assigned a gender or be neutral in this sense?
	Should companies adapt robots to signal different ethnic groups, cultures, and accents, or should they avoid doing so?
	Do some consumer groups have specific preferences for gendered or cultured service robots?
	How can companies avoid replicating gender or racial biases in their robot agents?
Robot notification	To what extent should customers be aware that they are interacting with a robot?
	How do consumers' perceptions, intentions, and actual behaviors vary when they interact with a service robot versus human service provider?
	When and how should companies notify customers that they are interacting with an automated agent?
Manipulability	Is there an optimal level of robot manipulability for customers?
	How might increased levels of psychological ownership minimize human discomfort in interactions with robots?
	Do some relevant consumer groups prefer to manipulate certain robot functions and variables to a greater or lesser extent?
Proactivity	What are the advantages and disadvantages of service robots' proactivity in human–robot encounters?
	Are customers more tolerant of human employees' proactivity than of automated agents' proactivity?
	In which service encounters or with which kind of customers should robots be more proactive or reactive?
Affect	Can robot recognition of human emotions or exhibited empathy facilitate human–robot interactions in a service encounter?
	Should automated agents pretend to have and express emotions in their service interactions with customers?
	In which service sectors and for which groups of customers is the inclusion of robot affective cues more suitable?
Formality	Is there an optimal, standardized level of service robot formality? In which service encounters or with which kinds of customers should automated agents use formal or informal language? Should robots adapt their verbal and body language when interacting with different customers (e.g. sense of humor, politeness)?
Customer features	
Technology readiness	To what extent does customers' technology readiness determine their acceptance of service robots?
	What roles do customers' optimism, innovativeness, discomfort, and insecurity related to technology have for the successful inclusion of robots in service settings?
	Which robot designs or service elements should companies integrate to address customers with lower technological abilities?
Age	As a general basis, are older customers more reluctant to use service robots than younger customers?
	How should robots be designed to provide assistive services for the elderly?
	To what extent do children and younger generations provide meaningful opportunities to test and develop service robots?
Gender	On a general basis, are women more reluctant to use service robots than men?
	Do men and women demand different robot design features?
	Do robots' exhibited genders need to match to customers' genders to facilitate service interactions?
Culture	To what extent does customer culture affect the acceptance of service robots?
	How should robot designs be adapted to each culture or different cultural values across service sectors?
	Which ethical concerns arise when customers from richer or poorer countries start to be served by robots?
Personality traits	To what extent do personality traits affect customers' adoption and use of service robots?

(*Continued*)

Table 1. Continued.

Framework path and subtopic	Research question
	How can robots adapt to customers with different levels of openness, conscientiousness, extraversion, agreeableness, and neuroticism?
	What other personal factors are at play in human–robot interactions?
Customer tier	How can service robots contribute to increase customer lifetime value?
	Do different customer tiers react differently to the introduction of robots in frontline service encounters?
	To what extent can service robots attract new customers?
Service encounter characteristics	
Information provision	Are robots that provide information and advice more welcomed by customers than those that perform other service functions?
	How might AI-based online assistants be improved to better satisfy customers' needs and demands?
	Are customers willing to share information with automated agents?
Involvement level	In a high involvement purchase setting, are customers more or less willing to interact with a service robot than with a human agent?
	How does customer involvement relate to service complexity and risk in a robot-provided service setting?
	Are highly involved customers more engaged with the service and ready to start using robot agents?
Failure and complaints	Will customers bring a complaint or service failure to a service robot?
	Do service robots have enough autonomy, flexibility, and affect to engage in service recovery?
	How should companies resolve service robot failures?
Product or service context	Should robots be introduced in product-oriented operations, before being launched to provide services?
	Do customers trust AI-driven browsers as tools that provide objective product comparisons?
	Which services should be the first to be completely provided by robots?
Transactional or relational services	Are service robots a better alternative than employees in standardized, transactional service settings?
	Are customers with an exchange orientation more prone to interact with service robots than those with a communal orientation?
	How can automated agents be designed to fulfill the relational demands and nature of many services?
Employee replacement or collaboration outcomes	In which cases should companies use robots to replace or else to collaborate with frontline employees?
	How will different groups of customers react to employees being replaced by service robots?
	Are customers willing to pay a premium price to interact with a human agent?
	Which advantages and service opportunities (e.g. opening hours, safety) might emerge as a consequence of robots performing frontline tasks?

Tay et al., 2014). Gender raises some sociological and ethical concerns too, such as whether gender features should be used to signal certain skills (Alesich & Rigby, 2017). Most of these issues likely arise with regard to robot culture and ethnicity signifiers too, suggesting the need to consider how the bias that appears in interpersonal interactions might be problematically replicated by robot designers and AI.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Daniel Belanche http://orcid.org/0000-0002-2291-1409
Carlos Flavián http://orcid.org/0000-0001-7118-9013

References

Aaltonen, I., Arvola, A., Heikkilä, P., & Lammi, H. (2017, March). Hello Pepper, may I tickle you?: Children's and adults' responses to an entertainment robot at a shopping mall. In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 53–54). ACM.

Aggarwal, P., & McGill, A. L. (2007). Is that car smiling at me? Schema congruity as a basis for evaluating anthropomorphized products. *Journal of Consumer Research*, *34*(4), 468–479.

Alesich, S., & Rigby, M. (2017). Gendered robots: Implications for our humanoid future. *IEEE Technology and Society Magazine*, *36*(2), 50–59.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, *85*, 183–189.

Babakus, E., Yavas, U., & Ashill, N. J. (2010). Service worker burnout and turnover intentions: Roles of person-job fit, servant leadership, and customer orientation. *Services Marketing Quarterly*, *32*(1), 17–31.

Bartneck, C., Suzuki, T., Kanda, T., & Nomura, T. (2007). The influence of people's culture and prior experiences with Aibo on their attitude towards robots. *AI & Society*, *21*(1-2), 217–230.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, forthcoming.

Belk, R. W. (2013). Extended self in a digital world. *Journal of Consumer Research*, *40*(3), 477–500.

Belk, R., Humayun, M. & Gopaldas, A. (2019). Consumer reception of new technologies. *International Journal of Business Anthropology*, forthcoming.

Bitner, M. J., Booms, B. H., & Tetreault, M. S. (1990). The service encounter: Diagnosing favorable and unfavorable incidents. *Journal of Marketing*, *54*(1), 71–84.

Brink, K. A., Gray, K., & Wellman, H. M. (2019). Creepiness creeps in: Uncanny valley feelings are acquired in childhood. *Child Development*, *90*(4), 1202–1214.

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. *International Journal of Social Robotics*, *1*(4), 319–330.

Brymer, R. A. (1991). Employee empowerment: A guest-driven leadership strategy. *Cornell Hotel and Restaurant Administration Quarterly*, *32*(1), 58–68.

Burleigh, T. J., Schoenherr, J. R., & Lacroix, G. L. (2013). Does the uncanny valley exist? An empirical test of the relationship between eeriness and the human likeness of digitally created faces. *Computers in Human Behavior*, *29*(3), 759–771. doi:10.1016/j.chb.2012.11.021

Čaić, M., Odekerken-Schröder, G., & Mahr, D. (2018). Service robots: Value co-creation and co-destruction in elderly care networks. *Journal of Service Management*, *29*(2), 178–205.

Canal, G., Escalera, S., & Angulo, C. (2016). A real-time human-robot interaction system based on gestures for assistive scenarios. *Computer Vision and Image Understanding*, *149*, 65–77.

Capek, K. (1920). *Rossum's Universal Robots*, Prague, CZ.

Carpenter, J., Davis, J. M., Erwin-Stewart, N., Lee, T. R., Bransford, J. D., & Vye, N. (2009). Gender representation and humanoid robots designed for domestic use. *International Journal of Social Robotics*, *1*(3), 261–265.

Cha, E., Kim, Y., Fong, T., & Mataric, M. J. (2018). A survey of nonverbal signaling methods for non-humanoid robots. *Foundations and Trends in Robotics*, *6*(4), 211–323.

Chen, C. W., Tseng, C. P., Lee, K. L., & Yang, H. C. (2011). Conceptual framework and research method for personality traits and sales force automation usage. *Scientific Research and Essays*, *6*(17), 3784–3793.

Chen, N. H., & Huang, S. C. T. (2016). Domestic technology adoption: Comparison of innovation adoption models and moderators. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *26*(2), 177–190.

Choi, J. K., & Ji, Y. G. (2015). Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692–702.

Colby, C. L., & Parasuraman, A. (2016, June 24). Service robotics: How ready are consumers to adopt and what drives acceptance? *25th Annual Frontiers in Services Conference*.

De Keyser, A., Köcher, S., Alkire, L., Verbeeck, C., & Kandampully, J. (2019). Frontline service technology infusion: Conceptual archetypes and future research directions. *Journal of Service Management*, *30* (1), 156–183.

Dholakia, U. M. (2001). A motivational process model of product involvement and consumer risk perception. *European Journal of Marketing*, *35*(11/12), 1340–1362.

Drury, J. L., Scholtz, J., & Yanco, H. A. (2003, October). Awareness in human-robot interactions. In *SMC'03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics. Conference Theme-System Security and Assurance (Cat. No. 03CH37483)* (Vol. 1, pp. 912–918). IEEE.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, *114*(4), 864–886.

Eyssel, F., & Kuchenbrandt, D. (2012). Social categorization of social robots: Anthropomorphism as a function of robot group membership. *British Journal of Social Psychology*, *51*(4), 724–731.

Fadhil, A., Schiavo, G., Wang, Y., & Yilma, B. A. (2018, May). The effect of emojis when interacting with conversational interface assisted health coaching system. In *Proceedings of the 12th EAI International Conference on Pervasive Computing Technologies for Healthcare* (pp. 378–383). ACM.

Fan, A., Wu, L., Miao, L., & Mattila, A. S. (2019). When does technology anthropomorphism help alleviate customer dissatisfaction after a service failure?–The moderating role of consumer technology self-efficacy and interdependent self-construal. *Journal of Hospitality Marketing & Management*, forthcoming.

Fernandez-Llamas, C., Conde, M. A., Rodríguez-Lera, F. J., Rodríguez-Sedano, F. J., & García, F. (2018). May I teach you? Students' behavior when lectured by robotic vs. Human teachers. *Computers in Human Behavior*, *80*, 460–469.

Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM*, *59*(7), 96–104.

Floh, A., & Treiblmaier, H. (2006). What keeps the e-banking customer loyal? A multigroup analysis of the moderating role of consumer characteristics on e-loyalty in the financial service industry. *Journal of Electronic Commerce Research*, *7*(2), 97–110.

Gácsi, M., Kis, A., Faragó, T., Janiak, M., Muszyński, R., & Miklósi, Á. (2016). Humans attribute emotions to a robot that shows simple behavioural patterns borrowed from dog behaviour. *Computers in Human Behavior*, *59*, 411–419.

Garrell, A., Villamizar, M., Moreno-Noguer, F., & Sanfeliu, A. (2017). Teaching robot's proactive behavior using human assistance. *International Journal of Social Robotics*, *9*(2), 231–249.

Genesys. (2019). U.S. Employers Expect Growth of Artificial Intelligence in the Workplace But Not Major Job Reductions. Retrieved from https://www.prnewswire.com/news-releases/us-employers-expect-growth-of-artificial-intelligence-in-the-workplace-but-not-major-job-reductions-300901926.html

Ghosh, S., & Pherwani, J. (2015, August). Designing of a natural voice assistants for mobile through user centered design approach. In *International Conference on Human-Computer Interaction* (pp. 320–331). Springer, Cham.

Giebelhausen, M. D., Robinson, S. G., & Cronin, J. J. (2011). Worth waiting for: Increasing satisfaction by making consumers wait. *Journal of the Academy of Marketing Science*, *39*(6), 889–905.

GoGulf. (2018). The rise of virtual digital assistance usage. Statistics and Trends. Retrieved from https://www.go-gulf.com/blog/virtual-digital-assistants/

Goldberg, L. R. (1990). An alternative "description of personality": the big-five factor structure. *Journal of Personality and Social Psychology*, *59*(6), 1216–1229.

Gong, L., & Nass, C. (2007). When a talking-face computer agent is half-human and half-humanoid: Human identity and consistency preference. *Journal of Human Communication Research*, *33*(2), 163–193.

Goodchild, A., & Toy, J. (2018). Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO2 emissions in the delivery service industry. *Transportation Research Part D: Transport and Environment*, *61*, 58–67.

Grant, A. M., Parker, S., & Collins, C. (2009). Getting credit for proactive behavior: Supervisor reactions depend on what you value and how you feel. *Personnel Psychology*, *62*(1), 31–55.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157–169.
Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010). Relating conversational expressiveness to social presence and acceptance of an assistive social robot. *Virtual Reality*, *14*(1), 77–84.
Hiroi, Y., & Ito, A. (2009). Effect of the size factor on psychological threat of a mobile robot moving toward human. *KANSEI Engineering International*, *8*(1), 51–58.
Hofstede, G. (n.d.). The 6 dimensions model of national culture. Retrieved from https://www.hofstede-insights.com/country-comparison/
Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172.
Hudson, J., Orviska, M., & Hunady, J. (2017). People's attitudes to robots in caring for the elderly. *International Journal of Social Robotics*, *9*(2), 199–210.
International Federation of Robotics. (2016). Classification of service robots by application areas, https://www.ifr.org/img/office/Service_Robots_2016_Chapter_1_2.pdf
International Federation of Robotics. (2018, October). *World robotics report 2018*. Press conference summary, Tokyo. Retrieved from https://ifr.org/free-downloads/
Ivanov, S., Webster, C., & Garenko, A. (2018). Young Russian adults' attitudes towards the potential use of robots in hotels. *Technology in Society*, *55*, 24–32.
Johnston, R., & Fern, A. (1999). Service recovery strategies for single and double deviation scenarios. *The Service Industries Journal*, *19*(2), 69–82.
Jörling, M., Böhm, R., & Paluch, S. (2019). Service robots: Drivers of perceived responsibility for service outcomes. *Journal of Service Research*, 1094670519842334.
Jussila, I., Tarkiainen, A., Sarstedt, M., & Hair, J. F. (2015). Individual psychological ownership: Concepts, evidence, and implications for research in marketing. *Journal of Marketing Theory and Practice*, *23*(2), 121–139.
Kiesler, S., Powers, A., Fussell, S. R., & Torrey, C. (2008). Anthropomorphic interactions with a robot and robot–like agent. *Social Cognition*, *26*(2), 169–181.
Kim, K. J., Park, E., & Sundar, S. S. (2013). Caregiving role in human–robot interaction: A study of the mediating effects of perceived benefit and social presence. *Computers in Human Behavior*, *29*(4), 1799–1806.
Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., … De Keyser, A. (2017). "Service Encounter 2.0": An investigation into the roles of technology, employees and customers. *Journal of Business Research*, *79*, 238–246.
Lim, A., & Okuno, H. G. (2015). A recipe for empathy. *International Journal of Social Robotics*, *7*(1), 35–49.
Lin, C. H., Liu, E. Z. F., & Huang, Y. Y. (2012). Exploring parents' perceptions towards educational robots: Gender and socio-economic differences. *British Journal of Educational Technology*, *43*(1), E31–E34.
Liu, K., Xiong, C. H., He, L., Chen, W. B., & Huang, X. L. (2018). Postural synergy based design of exoskeleton robot replicating human arm reaching movements. *Robotics and Autonomous Systems*, *99*, 84–96.
Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, *80*, 36–51.
MacDorman, K. F., & Ishiguro, H. (2006). The uncanny advantage of using androids in cognitive and social science research. *Interaction Studies*, *7*(3), 297–337.
MacDorman, K. F., Vasudevan, S. K., & Ho, C. C. (2009). Does Japan really have robot mania? Comparing attitudes by implicit and explicit measures. *AI & Society*, *23*, 485–510.
Makatchev, M., Simmons, R., Sakr, M., & Ziadee, M. (2013, March). Expressing ethnicity through behaviors of a robot character. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction* (pp. 357–364). IEEE Press.
Marinova, D., de Ruyter, K., Huang, M. H., Meuter, M. L., & Challagalla, G. (2017). Getting smart: Learning from technology-empowered frontline interactions. *Journal of Service Research*, *20*(1), 29–42.
Marlow, S., Taylor, S., & Thompson, A. (2010). Informality and formality in medium-sized companies: Contestation and synchronization. *British Journal of Management*, *21*(4), 954–966.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12–12.
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. *Journal of Marketing Research*, *56*(4), 535–556.
Mick, D. G., & Fournier, S. (1998). Paradoxes of technology: Consumer cognizance, emotions, and coping strategies. *Journal of Consumer Research*, *25*(2), 123–143.
Moon, H., Miller, D. R., & Kim, S. H. (2013). Product design innovation and customer value: Cross-cultural research in the United States and Korea. *Journal of Product Innovation Management*, *30*(1), 31–43.
Mori, M. (1970). The uncanny valley. *Energy*, *7*(4), 33–35.
Mourey, J. A., Olson, J. G., & Yoon, C. (2017). Products as pals: Engaging with anthropomorphic products mitigates the effects of social exclusion. *Journal of Consumer Research*, *44*(2), 414–431.
Nijssen, E. J., Hillebrand, B., Vermeulen, P. A., & Kemp, R. G. (2006). Exploring product and service innovation similarities and differences. *International Journal of Research in Marketing*, *23*(3), 241–251.
Nijssen, E. J., Schepers, J. J., & Belanche, D. (2016). Why did they do it? How customers' self-service technology introduction attributions affect the customer-provider relationship. *Journal of Service Management*, *27*(3), 276–298.
Obaid, M., Salem, M., Ziadee, M., Boukaram, H., Moltchanova, E., & Sakr, M. (2016, October). Investigating effects of professional status and ethnicity in human-agent interaction. In *Proceedings of the Fourth International Conference on Human Agent Interaction* (pp. 179–186). ACM.
Onorato, D. A. (2018). Robots, unions, and aging: Determinants of robot adoption evidence from OECD countries. *Atlantic Economic Journal*, *46*(4), 473–474.
Pagallo, U. (2018). Vital, Sophia, and Co.—The quest for the legal personhood of robots. *Information*, *9* (9), 230.
Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307–320.
Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74.
Pierce, J. L., Kostova, T., & Dirks, K. T. (2001). Toward a theory of psychological ownership in organizations. *Academy of Management Review*, *26*(2), 298–310.
Prentice, C., Dominique Lopes, S., & Wang, X. (2019). Emotional intelligence or artificial intelligence–an employee perspective. *Journal of Hospitality Marketing & Management*, forthcoming.
Pulido, J. C., González, J. C., Suárez-Mejías, C., Bandera, A., Bustos, P., & Fernández, F. (2017). Evaluating the child–robot interaction of the naotherapist platform in pediatric rehabilitation. *International Journal of Social Robotics*, *9*(3), 343–358.
Qiu, H., Li, M., Shu, B., & Bai, B. (2019). Enhancing hospitality experience with service robots: The mediating role of rapport building. *Journal of Hospitality Marketing & Management*, forthcoming.
Rafaeli, A., Altman, D., Gremler, D. D., Huang, M. H., Grewal, D., Iyer, B., … de Ruyter, K. (2017). The future of frontline research: Invited commentaries. *Journal of Service Research*, *20*(1), 91–99.
Rajan, K., & Saffiotti, A. (2017). Towards a science of integrated AI and robotics. *Artificial Intelligence*, *247*, 1–9.
Rau, P. P., Li, Y., & Li, D. (2009). Effects of communication style and culture on ability to accept recommendations from robots. *Computers in Human Behavior*, *25*(2), 587–595.
Rioux, S. M., & Penner, L. A. (2001). The causes of organizational citizenship behavior: A motivational analysis. *Journal of Applied Psychology*, *86*(6), 1306–1314.
Rosenthal-von der Pütthen, A. M., & Kramer, N. C. (2014). How design characteristics of robots determine evaluation and uncanny valley related responses. *Computers in Human Behavior*, *36*, 422–439.
Shah, H., Warwick, K., Vallverdú, J., & Wu, D. (2016). Can machines talk? Comparison of Eliza with modern dialogue systems. *Computers in Human Behavior*, *58*, 278–295.
Shamekhi, A., Czerwinski, M., Mark, G., Novotny, M., & Bennett, G. A. (2016, September). An exploratory study toward the preferred conversational style for compatible virtual agents. In *International Conference on Intelligent Virtual Agents* (pp. 40–50). Springer, Cham.
Sharma, A., & Pillai, K. G. (2003). The impact of transactional and relational strategies in business markets: An agenda for inquiry. *Industrial Marketing Management*, *32*(8), 623–626.

SoftBank Robotics. (2019). Corporate website. Retrieved from https://www.softbankrobotics.com/emea/en

Song, A., Wu, C., Ni, D., Li, H., & Qin, H. (2016). One-therapist to three-patient telerehabilitation robot system for the upper limb after stroke. *International Journal of Social Robotics*, *8*(2), 319–329.

Stroessner, S. J., & Benitez, J. (2019). The social perception of humanoid and non-humanoid robots: Effects of gendered and machinelike features. *International Journal of Social Robotics*, *11*(2), 305–315.

Takanishi, A. (2000). An anthropomorphic robot head having autonomous facial expression function for natural communication with humans. In J. M. Hollerbach & D. E. Koditschek (Eds.), *Robotics research* (pp. 297–303). London: Springer.

Takayama, L., & Pantofaru, C. (2009, October). Influences on proxemic behaviors in human-robot interaction. In 2009 *IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 5495–5502). IEEE.

Tay, B., Jung, Y., & Park, T. (2014). When stereotypes meet robots: The double-edge sword of robot gender and personality in human–robot interaction. *Computers in Human Behavior*, *38*, 75–84.

Thimmesch-Gill, Z., Harder, K. A., & Koutstaal, W. (2017). Perceiving emotions in robot body language: Acute stress heightens sensitivity to negativity while attenuating sensitivity to arousal. *Computers in Human Behavior*, *76*, 59–67.

Tinwell, A., Grimshaw, M., Nabi, D. A., & Williams, A. (2011a). Facial expression of emotion and perception of the uncanny valley in virtual characters. *Computers in Human Behavior*, *27*(2), 741–749.

Tinwell, A., Grimshaw, M., & Williams, A. (2011b). The uncanny wall. *International Journal of Arts and Technology*, *4*(3), 326–341.

Torrey, C., Fussell, S., & Kiesler, S. (2013, March). How a robot should give advice. In *Proceedings of the 8th ACM/IEEE international conference on human-robot interaction* (pp. 275–282). IEEE Press.

Tussyadiah, I. P., & Park, S. (2018). Consumer evaluation of hotel service robots. In B. Stangl & J. Pesonen (Eds.), *Information and communication technologies in tourism* (pp. 308–320). Cham: Springer.

Van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research*, *20*(1), 43–58.

Van Pinxteren, M. M., Wetzels, R. W., Rüger, J., Pluymaekers, M., & Wetzels, M. (2019). Trust in humanoid robots: Implications for services marketing. *Journal of Services Marketing*, forthcoming.

Vaussard, F., Fink, J., Bauwens, V., Rétornaz, P., Hamel, D., Dillenbourg, P., & Mondada, F. (2014). Lessons learned from robotic vacuum cleaners entering the home ecosystem. *Robotics and Autonomous Systems*, *62*(3), 376–391.

Wada, K., & Shibata, T. (2007). Living with seal robots—Its sociopsychological and physiological influences on the elderly at a care house. *IEEE Transactions on Robotics*, *23*(5), 972–980.

Walters, M. L., Syrdal, D. S., Dautenhahn, K., Te Boekhorst, R., & Koay, K. L. (2008). Avoiding the uncanny valley: Robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion. *Autonomous Robots*, *24*(2), 159–178.

Wieseke, J., Geigenmüller, A., & Kraus, F. (2012). On the role of empathy in customer-employee interactions. *Journal of Service Research*, *15*(3), 316–331.

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. *Journal of Service Management*, *29*(5), 907–931.

Woods, S., Dautenhahn, K., Kaouri, C., te Boekhorst, R., Koay, K. L., & Walters, M. L. (2007). Are robots like people?: Relationships between participant and robot personality traits in human–robot interaction studies. *Interaction Studies*, *8*(2), 281–305.

Yu, C. E. (2019). Humanlike robots as employees in the hotel industry: Thematic content analysis of online reviews. *Journal of Hospitality Marketing & Management*, forthcoming.

Yu, C. E., & Ngan, H. F. B. (2019). The power of head tilts: Gender and cultural differences of perceived human vs human-like robot smile in service. *Tourism Review*, *74*(3), 428–442.

Zhang, H., Liang, X., & Wang, S. (2016). Customer value anticipation, product innovativeness, and customer lifetime value: The moderating role of advertising strategy. *Journal of Business Research*, *69*(9), 3725–3730.