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Automated social presence in AI: Avoiding consumer psychological tensions to improve service value

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ABSTRACT

Consumers are increasingly embracing robots and AI. This has led them to suffer psychological tensions in their AI experiences (e.g., data capture, classification, delegation and social experiences). This exploratory research proposes that AI with higher perceived automated presence (sense of being with another being) alleviates psychological tensions. This in turn leads to consumer perceptions of higher functional and social value and higher future use intention. A study into service robots (n = 331) supported the proposal that consumers' perceptions of greater automated social presence in service robots makes them feel understood rather than misunderstood, empowered rather than replaced and connected rather than alienated, which increases their functional and social value perceptions and intention to use robots in the future. The impact of automated social presence on social experience is higher for consumers with a higher need for social interaction. This research lends weight to some theoretical proposals made in previous literature that were, at that point, empirically unexplored.

1. Introduction

Service providers are introducing artificial intelligence (AI), robotics and other automation technologies to increase productivity and provide consumers with enhanced options (Pitardi et al., 2022). Companies like Amazon rely extensively on algorithms to develop personalized offerings and use robots to prepare shipments and machine learning to coordinate deliveries. The result is they achieve higher levels of efficiency than purely human-based companies. In 2022, the sales of professional service robots grew by 48 % worldwide (IFR, 2023). Experts foresee that some sectors, for example, financial services, will be completely automated by 2030 and that, by then, the economic impact of AI on national GDP could be around 20 % in countries such as China and the USA (PwC, 2022). Although automation is supposed to enhance consumerś experiences and improve peoples' lives by providing greater levels of efficiency (Xiao and Kumar, 2021), the reality is that the technological impact on users' psychological well-being is frequently just the opposite. Indeed, an increasing amount of evidence suggests that a decrease in society's welfare is the worst unintended consequence of the introduction of AI and service robots (e.g., addiction to AI friendship apps [Marriott and Pitardi, 2023]; human rights issues associated with ChatGPT and other AI, including algorithmic transparency, vulnerability, bias and discrimination, lack of accountability, privacy and concerns about where liability lies [Rodrigues, 2020]); this demands greater academic attention.

Previous robot-focused studies have widely investigated the role of anthropomorphism (i.e., robots' human-like cues) in the understanding of consumer acceptance of AI-led devices (see Blut et al., 2021 for a review) and consumer well-being (Loureiro et al., 2021; Akdim et al., 2023). Offering further insight into this issue, the concept of automated social presence (ASP) has emerged recently in the literature. ASP has been defined as "the extent to which machines (e.g., robots) make consumers feel that they are in the company of another social entity" (van Doorn et al., 2017, p. 44). This novel concept is particularly important because it switches the focus of the topic from the robots features (i.e., human-like characteristics in anthropomorphized robots) to the consumer's subjective perceptions (i.e., being in the presence of other being), which may be more related to the psychological tensions experienced by consumers in service robot encounters. Nevertheless, despite ASP's potential impact on consumers' experiences with service robots, little research has taken place into the concept, due to its novelty, most of it being theoretical (van Doorn et al., 2017); ASP has also

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inaccurately been used as a synonym of anthropomorphism (Čaić, et al., 2020; Yoganathan et al., 2021), ignoring the impact that it may have on consumers' self-evaluations of their well-being. In this regard, our proposal differs from the recent, scarce, empirical research into ASP in terms of increasing chatbot trust and online shopping (Konya-Baumbach et al., 2023), and helping consumers face embarrassing situations when dealing with frontline services (Holthöwer and van Doorn, 2023).

Taking a complementary approach, and moving beyond positivistic technology adoption models (see Hollebeek and Belk, 2021, for a review), some research has addressed challenges that AI might pose by investigating the psychological tensions that develop in human-AI interactions (Gill, 2020; Puntoni et al., 2021). These psychological problems seem to be particularly important in the context of AI-consumer interactions because the technology is more disruptive than others seen in previous technological revolutions (Bock et al., 2020; Belk et al., 2023). Some initial insight into this emerging approach is provided in a labor setting, where theoretical (e.g., Xiao and Kumar, 2021) and empirical studies (Beane, 2019) have explored employees' role stressors when they have had to deal with AI (e.g., disempowerment from being substituted). From a consumer perspective, Puntoni et al. (2021) proposed a theoretical framework that categorized the psychological tensions that consumers may feel based on their subjective AI experiences, suggesting that consumers may perceive AI as positive or negative. In particular, the framework identifies four dimensions of the consumer's experience of AI: data capture (i.e., feeling served or exploited), classification (i.e., feeling understood or misunderstood), delegation (i.e., feeling empowered or replaced) and social experience (i.e., feeling connected or alienated). While the above demonstrates that some interest has been shown in the topic, the scarce research that has been carried out into the psychological tensions that AI can cause consumers is theoretical and calls for empirical analyses of the impact of the technology on their well-being, including its potential downsides and ethical risks (Lu et al., 2020; Puntoni et al., 2021).

Thus, taking ASP as a basis, and drawing on the theoretical AI experience framework of Puntoni et al., (2021), the present (exploratory) study aims to address this research gap. Our proposal addresses the issue by focusing on frontline service robots (waiters) in the hospitality sector, an area of increasing interest among scholars and practitioners (Pitardi et al., 2022; van Doorn et al., 2023). Sales of service robots to the hospitality sector grew by 125 % in 2022 (IFR, 2023), and the market is foreseen to flourish further, with revenues expected to reach 1.97 billion USD by 2028, from 324 million in 2022 (Arizton, 2023). Our study analyzes robot waiters because they are affordable and increase restaurants' efficiency (Belanche et al., 2021a), and because their disruptive nature impacts on those key consumer behaviors and emotions that are the domain of service managers (Schepers et al., 2022). Based on the (still limited) knowledge of ASP (van Doorn et al., 2017; Konya-Baumbach et al., 2023), and to expand the research into this new concept, we propose that consumerś feelings of ASP may lessen the psychological tensions they might experience in their interactions with robots. More specifically, the link between the ASP concept and psychological tensions suggests that consumers' perceptions that their robot-based experiences are characterized by higher ASP could make them feel served rather than exploited, understood rather than misunderstood, empowered rather than replaced and connected rather than alienated. Therefore, ASP may be crucial in helping managers avoid the unintended consequences of using robots in frontline services, such as the exertion of a negative impact on consumers' psychological well-being (Lu et al., 2020; Loureiro et al., 2021): companies, and society as whole, may benefit from a better understanding of the phenomenon. The managerial significance of our approach is based on previous literature that has proposed that psychological tensions affect consumers' choices (Liu & Hogg, 2018) and relationships with service providers (Fang et al., 2011).

Complementing our model from a service marketing approach, and following recent studies on service robot introduction (Belanche et al., 2021b), we analyze the influence that these AI experiences (the release of these psychological tensions) may have on service value perceptions, including both functional value (i.e., performance) and social value (i.e., social image), which in turn are proposed as determinants of consumerś intentions to use service robots. In addition, we propose that the influence of ASP on AI experiences varies among consumers, that is, this influence is more important for consumers with higher needs for social interaction. This is formally hypothesized as a moderating effect.

The novelty of the proposal means that our exploratory work contributes to AI research in several ways. First, it is proposed that ASP is better able to explain robotś impacts on consumers' well-being than is anthropomorphism. This new ASP concept is almost unexplored in previous research, despite its potential importance in frontline settings. Second, our research expands an emerging research stream examining the harmful and unintended consequences of the use of AI in services, particularly the psychological tensions provoked in consumers by AI experiences. Thus, we empirically analyze, to assess the influence of ASP on consumerś AI experiences, the effects these psychological tensions exert in a specific service robot setting. We also examine how these tensions affect consumers' service value perceptions and subsequent use intentions. Third, our study disentangles the relationships between these variables and raises important managerial implications that can help companies alleviate the psychological tensions provoked in consumers by their AI experiences (e.g., by increasing ASP), and identifies which segmentation strategies they might implement (e.g., targeting consumers with higher need for social interaction). Finally, our research opens a new research avenue that examines consumers' self-reflections about their role in their interactions with the seemingly unstoppable AI (e.g., generative AI, chatbots, sex robots) and encourages scholars to further investigate the spread of these technology-based tensions in society.

2. Literature review

2.1. From anthropomorphism to automated social presence

As noted previously, ASP has been defined as the capacity of AI/machines to make people sense they are with other people (Biocca et al., 2003; van Doorn et al., 2017). Social interactions are not reserved exclusively to humans, that is, technologies can mimic humans in appearance and behavior (Čaić, et al., 2020). These technology-human contacts are often described as quasi-social interactions. Some authors argue that ASP is not solely technology focused but, indeed, is also a product of humanś subjective perceptions (Biocca et al., 2003).

Even prior to the rise of AI, research had acknowledged that humans respond socially to technology (e.g., computers; Reeves and Nass, 1996). However, this social response is particularly noteworthy in interactions with AI and robots because these novel agents can listen, converse and read emotional cues and respond accordingly (Čaić, et al., 2020), perhaps displaying appropriate artificial emotions (Belk, 2023). Since van Doorn et al. (2017) proposed that ASP is key in consumer engagement in marketing and service research, only a few studies have investigated the concept, often linking it to anthropomorphism (Čaić, et al., 2020; Yoganathan et al., 2021). Anthropomorphism refers to the extent to which consumers perceive service robots as humanlike (Blut et al., 2021), and has been shown to be based on consumers' attributions of the technology's human features (e.g., physical appearance, name, face, free will; Belk et al., 2023). In contrast, ASP is a subjective feeling of being with someone else (i.e., the technology is perceived as a social entity with a social role). Although the link between the two concepts is intuitive and straightforward (i.e., anthropomorphic cues lead to perceptions of ASP; Blut et al., 2021), they should not be confused conceptually or in their operationalization. This distinction suggests that further research is needed to clarify the distinct role of ASP as an element that satisfies consumers' social needs and enriches their social interactions (van Doorn et al., 2017; Blut et al., 2021).

The scare research that has examined this emerging concept has proposed that ASP influences the consumer's views of the service process and its outcomes (Van Doorn et al., 2017). More specifically, some authors have argued that high levels of ASP improve the consumeŕs experience and consumer-related outcomes, such as satisfaction, loyalty, engagement and well-being (van Doorn et al., 2017; Yoganathan et al., 2021). These beneficial effects may be grounded on the theoretical foundations of social presence (i.e., physical or computer mediated, Short et al., 1976; Konya-Baumbach et al., 2023), social cognition (i.e., warmth, competence; Fiske et al., 2007) and psychological ownership (i.e., higher control, belonginess; Pierce et al., 2001). However, due to the novelty of AI-based services, knowledge about the intended or unintended consequences of ASP for consumers, in general, and on their well-being, in particular, is still very limited.

2.2. AI-related psychological tensions

In addition to developing understanding of technology acceptance aspects, there is a need to examine how consumers feel about the introduction of AI, given that it is more disruptive than previously developed technologies (e.g., its unconventional capabilities), and to assess how to manage its integration into people's lives (Bock et al., 2020; Belk et al., 2023). In this regard, some research has started to investigate the psychological tensions/anxieties that consumers experience in their human-AI interactions during the consumer journey (Gill, 2020; Lu et al., 2020; Puntoni et al., 2021).

The framework recently proposed by Puntoni et al. (2021) is particularly appropriate to take the issue forward given that it provides a bridge between the advantages of AI (a neutral tool with higher efficiency and accuracy) and the social and psychological challenges that affect consumers when faced with AI. The model represents an advance in the knowledge of AI as it clarifies some critical issues raised by the previous literature in relation to the technology, such as its limited ability to think out-of-the-box, its personalization capability (Wirtz et al., 2018), its use to augment or, even, replace human skills (Lariviére et al., 2017) and its effects on the autonomy of the user's ability to choose (Wertenbroch et al., 2020). Puntoni et al. (2021) proposed, based on their analysis, that consumers who benefit from AI services, nonetheless, face psychological and social costs that merit further analysis and understanding. The framework assumes that AI collects, analyzes and stores data to predict, produce and communicate with consumers. This sophisticated intelligence may cause, in the consumer, affective reactions and attributions (e.g. based on the symbolic aspects that AI raises for each consumer) in the subjective AI experience undergone by consumers. In particular, these authors proposed that four AI capabilities lead to four AI experiences which create psychological tensions in the consumer.

We propose that Puntoni et al.'s (2021) framework can be applied to consumers' robot experiences since service robots are AI-led and require increasingly sophisticated analytical, and even quasi-emotional, abilities (Belk et al., 2023; Schepers et al., 2022). Therefore, consumers' experiences with robots may involve psychological positive feelings/benefits (i.e., feeling served, understood, empowered, connected) or negative feelings/costs (i.e., feeling exploited, misunderstood, replaced, alienated). These are formally hypothesized in the next section.

3. Research model and hypotheses formulation

3.1. The impact of automated social presence on robot experience

van Doorn et al. (2017) proposed that introducing ASP into service encounters helps consumers develop a perception of conspecific presence, which suggests that consumers who feel ASP in their interactions with a technology expect it to behave more similarly to a human than would a technology lacking ASP. In this regard, it has been suggested that robots which generate higher levels of ASP are perceived as being more trustworthy, sociable and able to encourage consumers to bond with them (van Doorn et al., 2017).

ASP can make robots more visible and attractive, arousing consumers' interest, attention and desire for manipulability (Jussila et al., 2015). Higher levels of ASP are associated with higher levels of robot competence (e.g., capable, skillful, Ruiz-Equihua et al., 2023) and service receptiveness (e.g., affiliation, helpfulness, van Doorn et al., 2017), that can cause consumers to develop perceptions that they are being well served (AI listening capacity). Previous literature has suggested that robots that develop an understanding of their useŕs abilities, intentions and beliefs can develop social and emotional connections with them (Cabibihan et al., 2014). Indeed, an additional advantage of ASP is that human-AI interactions may result in mutual learning that is truly collaborative and socially enriching (van Doorn et al., 2017); this suggests that higher levels of ASP can lead to higher consumer perceptions that robots understand them (AI classification experience). Robots scoring high in ASP may also have the capacity to assist humans and adopt norms and behaviors in accordance with their social roles (Wykowska et al., 2014), so that higher ASP would lead consumers to feel more empowered (AI predicting capacity). Complementarily, ASP has been linked to service attractiveness (e.g., a higher motivation to be associated with appealing, agreeable, funny and empathetic agents, Damiano et al., 2015) and perceptions that robots are warm and attractive (e.g., friendly, kind, sociable, Ruiz-Equihua et al., 2023); these aspects create a higher probability of social engagement (Yoganathan et al., 2021; van Doorn et al., 2017). Consequently, higher levels of ASP can lead consumers to feel more connected (AI interacting capability). Our first hypothesis formally proposes these relationships.

H1. ASP positively affects a) listening experience (feeling served rather than exploited), b) classification experience (feeling understood rather than misunderstood), c) delegation experience (feeling empowered rather than replaced) and d) social experience (feeling connected rather than alienated).

3.2. The impact of robot experience on service value

3.2.1. Listening experience: Served vs. Exploited

Puntoni et al. (2021) analyzed AI's listening capability (i.e., to collect data in the environments where consumers live) and capacity to capture, store and utilize data. Consumers benefit due the better service that the technology can provide based on the data (e.g., offering additional services based on previous behaviors). However, consumers remain uncertain about how their data is managed, and by whom (Zuboff, 2019). In the sociological context, in a surveillance society, consumers perceive they are being monitored and experience a loss of control of their personal information when they are targeted by programmatic advertising. The psychological consequences are that consumers who are satisfied with higher levels of AI-based customization will feel better served, while consumers who perceive a lack of transparency in the use of, and loss of control of, their data, will feel exploited by AI, which can evoke negative affect, moral outrage and reactance (to restore control).

Given that individuals seek pleasure and to avoid pain (Bagozzi et al., 2016), positive and negative feelings in service experiences are paramount in determining perceptions of service value, particularly in human-robot interactions in service experiences (Schepers et al., 2022). Specifically, in this study we focus on functional value, that is, the utility customers derive from the quality and performance of a service, and social value, the utility consumers derive from a service's ability to enhance their social self-concepts (Sweeney & Soutar, 2001). The literature examining both traditional and technology-driven service experiences proposes that consumers value service agents with abilities that can provide better service (Bitner et al., 1990; 2000). Frontline agents who listen to consumers, ask questions and hear them out are perceived as being proficient problem-solvers that make consumers feel better (Gruber, 2011). Thus, for practical and social reasons, consumers prefer frontline agents who listen to them to better satisfy their needs

(Bitner et al., 1990; Belanche et al., 2021b). Consequently, we formulate the second hypothesis:

H2. Listening experience (feeling served rather than exploited) positively affects a) perceived functional value and b) perceived social value.

3.2.2. Classification experience: Understood vs. Misunderstood

Puntoni et al., (2021) addressed AI's predicting capability, which relates to the consumer's classification experience. AÍs ability to ultra-customize service offerings helps maximize consumer's engagement, feelings of personal importance and satisfaction (Kumar et al., 2019), which leads them to feel they are understood. However, AÍs ability to "predict" their preferences may cause consumers to infer that they are being classified as a particular type of person. For instance, consumers may welcome suggestions about which Netflix broadcasts to watch, but they may also perceive that the AI is excessively guiding and focusing them to watch "what other people like me watch". When this psychological tension leads consumers to develop a negative perception of this AI predictive capability, they may feel misunderstood (rather than understood), classified and frustrated, which may harm their individual free will perceptions. In addition, consumers may perceive they are being discriminated against, in terms of the messages aimed at them, based on their assignment to a particular category, or that they have been inaccurately assigned to a particular category.

In this regard, literature examining offline settings has proposed that consumers prefer to interact with frontline agents that understand, and show empathy for, consumers (Bitner et al., 1990), in particular, agents who take the consumer's perspective to provide a personalized answer (Gruber, 2011). In technology-led services, previous studies have shown that consumers may feel that their demands are understood or misunderstood, this being a critical factor in the determination of service value in both utilitarian and social terms (Belanche et al., 2021b; Schepers et al., 2022). Consequently, the third hypothesis formally proposes:

H3. Classification experience (feeling understood rather than misunderstood) positively affects a) perceived functional value and b) perceived social value.

3.2.3. Delegation experience: Empowered vs. Replaced

Puntoni et al. (2021) argued that AI's production capability can create psychological tensions. When automation is involved in the production and co-creation of value, consumers undergo a delegation experience. Google Assistant making a hairdresser's appointment for its user, and ChatGPT writing an email based on its user's prompts, are examples of this delegation experience. These experiences are often satisfactory/useful because they allow consumers to focus on other tasks, or enjoy free time, increasing their feelings of empowerment. However, as observed in literature examining AI in the workplace, this delegation experience may also lead to feelings of being replaced (Beane, 2019; Xiao and Kumar, 2021). In a sociological view of a transhumanist technology, people feel the threat of being replaced because AI and robots have abilities than exceed their own (Belk et al., 2023) and believe service standards are at risk (e.g., less employment, lack of human touch, Akdim et al., 2023). In addition, technology should not deprive humans of a sense of accomplishment in the value co-creation based on their decisions and consumption experiences.

The literature on the introduction of AI into the workplace has suggested that technologies that enhance employee's feelings of empowerment provide greater value for them functionally (e.g., performance) and socially (e.g., happiness, self-esteem), whereas being replaced by AI leads to negative perceptions about this disruptive phenomenon (Loureiro et al., 2023). Focusing on consumers from a cost-benefit paradigm perspective, value involves a trade-off between perceived costs and benefits (Brady et al., 2005); thus, consumers balance costs against benefits when forming their service value perceptions (e.g., Kleijnen et al., 2007). In this context, performance and social concerns are crucial for consumers' evaluations of AI-led services (Belanche et al., 2023). In this regard, consumers who feel empowered (or replaced) by AI will perceive that the technology satisfies (or frustrates) their needs for self-esteem, competence and autonomy (Consiglio and van Osselaer, 2022). Thus, service value is enhanced when consumers feel they benefit from their AI experiences (i.e., empowered). In turn, if AI experiences result in the consumer suffering cost or harm (i.e., replaced), service value will be reduced. Thus:

H4. Delegation experience (feeling empowered rather than replaced) positively affects a) perceived functional value and b) perceived social value.

3.2.4. Social experience: Connected vs. Alienated

Finally, Puntoni et al. (2021) discussed AÍs interaction capability. Although they are dealing with a technology, people interacting with AI, robots and chatbots go through a social experience. Recent developments in social robotics are enabling service providers to offer comfortable and emotionally meaningful human-technology encounters (Belk, 2022; van Doorn et al., 2017). In the sociological context of humanized AI, some consumers feel socially connected to the technology, for example, when smart apps encourage consumers to increase their level of physical exercise (Gelbrich et al., 2021), and help older people with disabilities (Corbyn, 2021; Wu, 2019). However, consumers may also feel alienated by being served (or accompanied) by a technological rather than a human agent. This concern is particularly prevalent in Europe/Western countries where people live more in solitude and traditional social bonds may have been replaced by technologies (European Commission, 2018).

The service research literature has clearly established that frontline agents who engage consumers socially (rather than disregard them) make them feel better and are perceived as providing greater functional and social value (Bitner et al., 2000; Belanche et al., 2021b). Similarly, previous studies have suggested that frontline agents' friendliness, openness and authenticity contribute to consumer's perceptions of trust, reciprocity and being taken seriously (Gruber, 2011); this is consistent with the findings of other studies that showed that robots and other AI systems that lack affective and social skills alienate consumers and provide decreased utilitarian and socio-emotional value (Kipnis et al., 2022; Schepers et al., 2022). Consequently, we propose the following hypotheses:

H5. Social experience (feeling connected rather than alienated) positively affects a) perceived functional value and b) perceived social value.

3.3. Impact of functional and social value on intentions to use

In addition, we follow previous literature that suggested that offering service value is crucial for companies' medium- and long-term success (e.g., Belanche et al., 2021b; Hartnett, 1998; Albrecht, 1992). Service value perceptions reflect the consumer's overall assessment of the utility of a service based on his/her expectations and perceptions of what she gives and receives (Zeithaml, 1988), which may influence his/her decision-making (e.g., Belanche et al., 2021b). Specifically, higher service value implies that the ratio between what the consumer gets and what (s)he gives is increased, which provides him/her with reasons to use the service (Sweeney and Soutar, 2001). In particular, consumers who perceive greater functional value are more willing to use service robots to continue benefiting from their in-built qualities (e.g., efficiency, reliability). Analogously, consumers who perceive they receive greater social value will tend to use service robots more to put them in a positive light in the eyes of other people (Belanche et al., 2019). As a result, we expect that both functional and social dimensions will influence consumer's intentions to use service robots. Thus:

H6. Perceived functional value positively affects intention to use.

H7. Perceived social value positively affects intention to use.

3.4. The moderating effect of the need for social interaction

Finally, we propose that social interaction is a key consumer trait that reinforces the effects of ASP on AI experiences. The need for social

interaction has been defined as the degree to which human interaction in service encounters is important to consumers (e.g., Dabholkar, 1996). Belanche et al. (2021b) argued that, because of service robots' capacities to behave like human beings, social interaction may be especially important in understanding consumer reactions to these technologies.

Specifically, for those consumers with a high need for social interaction, contact with a human frontline employee is very important (Bitner et al., 1997). Thus, these particular consumers lack the intrinsic motivation to adopt technological alternatives to frontline employees (Dabholkar and Bagozzi, 2002). As ASP helps satisfy the consumer's social needs, and enriches his/her social interactions by making him/her sense they are with another person (van Doorn et al., 2017), this study posits that consumers with a higher need for social interaction will be more sensitive to increments in the ASP of robots because their technology-based service encounters will increasingly resemble the traditional human service provision that they strongly prefer (e.g., human receptiveness, attractiveness, van Doorn et al., 2017; Belanche et al., 2021b). In other words, the positive effects of ASP on AI experiences will be reinforced for consumers with a higher need for social interaction. Thus, we propose the following hypotheses (see Fig. 1):

H8. The consumer's need for social interaction moderates the effects of ASP on his/her AI experiences, such that the positive influence of ASP on feeling a) served, b) understood, c) empowered and d) connected will be greater for consumers with a higher need for social interaction.

4. Method

4.1. Data collection

To test the proposed model, we collected data using an online survey addressed at US consumers of service robots. The participants were recruited through a market research company; they received an incentive payment. Before completing the questionnaire, the participants were provided with information on the scientific purpose of the study and protection of their data, and they gave their explicit informed consent.

Following previous studies that used audiovisual content material of robot prototypes or currently deployed service robots (e.g., Belanche et al., 2021b), the participants first watched a video in which a humanoid service robot performed various tasks in a real restaurant (e.g., welcoming customers, making suggestions, serving customers). The names of the robot and the restaurant were not shown to the participants to avoid reputation bias (e.g., MacKenzie et al., 1986). Thereafter, to measure the research variables, the participants answered an online questionnaire featuring scales adapted from previous studies: ASP (van Doorn et al., 2017; Lin et al., 2021), need for social interaction (Dabholkar and Bagozzi, 2002), social and functional value (Yang and Jolly, 2009; Sweeney and Soutar, 2001) and intention to use (Belanche et al., 2021b). In addition, four items with semantic differential scales (Osgood, 1952) were adapted to the research context (based on the proposals made by Puntoni et al., 2021) to measure the four consumer AI experiences: data capture experience (served vs. exploited), classification experience (understood vs. misunderstood), delegation experience (empowered vs. replaced) and social experience (connected vs. alienated). The survey items were designed to obtain an overall evaluation of the psychological tension associated with the dimensions (Puntoni et al., 2021). To ensure a valid operationalization of the measures, we took steps to verify their face validity (Hardesty and Bearden, 2004). A set of experts in AI, service research and consumer behaviors evaluated the degree to which each item was representative of the construct of interest. Items that produced a high level of consensus (i.e., at least 80 % of the experts classified them as clearly, or somewhat, representative of the construct) were retained (Lichtenstein et al., 1990; Zaichkowsky, 1985). The final measurement scales are at Appendix 1.

Finally, the questionnaire included attention and item understanding checks, and several procedural remedies were followed to minimize common method bias (Podsakoff et al., 2003). For example, we ensured that there were no right or wrong answers and guaranteed the participants' anonymity; in addition, the questionnaire was designed to avoid item ambiguity, complicated syntax and vague concepts. For the

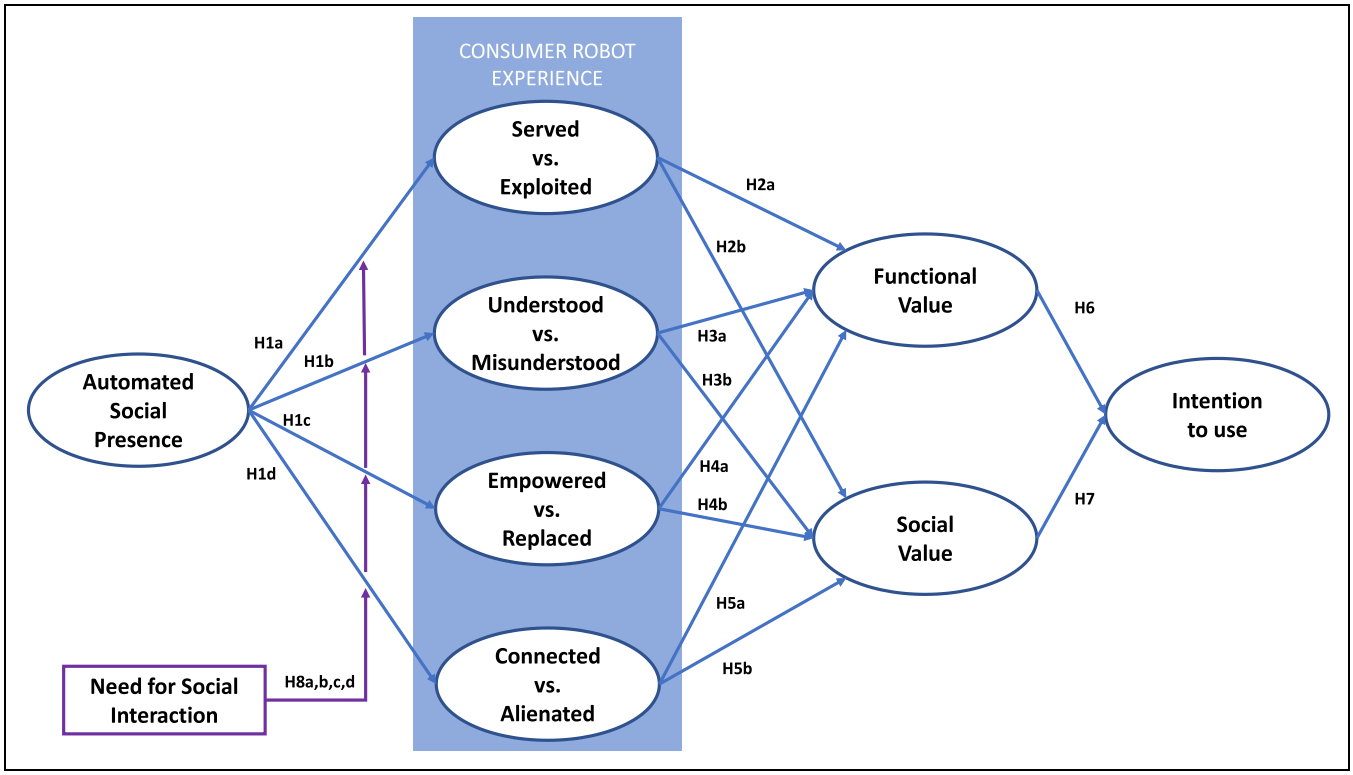

Fig. 1. Research model.

attention and item understanding checks, we used direct queries, such as "for this query, mark number 3 and move on to the following question" and logical statements, such as "I would rather eat a piece of fruit than a piece of paper", employing seven-point Likert-type response formats, from 1 ("completely disagree") to 7 ("completely agree") (e.g., Abbey and Meloy, 2017). A final question about the content of the video served to ensure that participants had paid attention.

The company sent us data from the 340 completed responses, but we had to remove nine of these from the sample because they failed one of the checks, thus, the final sample was 331 participants. The socio-demographic characteristics of the final sample were: gender (45.92 % male, 54.08 % female), age (<25 years, 16.31 %; 25–34 years, 14.50 %; 35–44 years, 30.21 %; 45–54 years, 14.50 %; 55–64 years, 18.13 %; 65 or older, 6.34 %) and education (7.85 % up to elementary/primary school; 25.68 % secondary/high school; 66.47 %, university studies). The sample is quite close to the US population in terms of gender and age (US Census Bureau, 2023), but included more individuals with university studies (41.93 % [US Census Bureau, 2019]); people with higher education levels are more prone to interact with service robots (e.g., Hudson et al., 2017).

4.2. Estimation procedure

Partial least squares (PLS) was used for the data analysis because it can handle data without multivariate normality (Hair et al., 2011) and is suitable for exploratory research and when the phenomenon under study is relatively new (Roldán and Sánchez-Franco, 2012), as in the case of service robots and consumer experiences with AI (Puntoni et al., 2021). In addition, due to its predictive nature (Davcik, 2014), PLS can help identify the consumer AI experiences that may be crucial to develop their intention to use service robots. Last, PLS is especially useful for testing complex models that simultaneously include several indirect and moderating effects (Davcik, 2014), as in the present study. To assess the significance of the paths and indicators we followed a non-parametric bootstrapping procedure with 10,000 subsamples, and no sign change (using SmartPLS 3.0 statistical software) (Ringle et al., 2015).

4.3. Measurement validation

First, we evaluated the reliability and convergent validity of the research constructs. We assessed whether the factor loadings were above the cut-off value of 0.7 (Henseler et al., 2009); one item of the ASP scale that did not reach this value was eliminated (see Appendix 1). Thereafter, we examined the Cronbach's alpha and composite reliability values, which were above their respective thresholds of 0.7 (Nunnally, 1978) and 0.65 (Jöreskog, 1971) for each reflective construct (Table 1). To assess convergent validity we confirmed that the average variance extracted (AVE) values were higher than 0.5 (Fornell and Larcker, 1981) (Table 1). Next, we assessed discriminant validity following three criteria: (1) we confirmed that the square roots of the latent variables' AVEs were higher than the inter-construct correlations (Fornell and Larcker, 1981); (2) we checked that the heterotrait–monotrait ratios of all correlations were lower than 0.85 (Henseler et al., 2015); and (3) we checked that the indicators' factor loadings were higher for their assigned constructs than for other variables. In addition, following Pavlou et al. (2007), it was confirmed that all constructs were distinct from each other, that is, the inter-construct correlations were well below the 0.90 threshold. These criteria, which can be seen in Table 1, support the discriminant validity of the variables.

Finally, even though we followed the study design recommendations of Podsakoff et al. (2003), we also conducted a full collinearity test to assess whether common method bias might affect the research model (Kock and Lynn, 2012). Following Kock and Lynn, (2012), we created a model where all the latent variables point at a random dummy variable (defined as a latent variable with a single indicator) and generated full variance inflation factors (FVIFs) for all the latent variables. AS all the factor-level FVIF values were lower than 3.3 (see Table 1), it can be concluded that the model is free of common method bias (Kock, 2015).

5. Results

The relationships proposed in the research model were analyzed using, again, SmartPLS 3.0 statistical software (Ringle et al., 2015). Fig. 2 shows the path estimates and their significance. The global fit of the structural model was evaluated using the standardized root mean residual (SRMR). We obtained a value of 0.044, which indicates the model has adequate global fit (as it is below the cut-off value 0.08) (Hu and Bentler, 1998).

As to the tests of the research hypotheses, we first evaluated how ASP affects consumers' experiences with AI. Supporting H1b, H1c and H1d, ASP makes consumers feel more understood ($\beta = 0.267$, $p < 0.01$), empowered ($\beta = 0.264$, $p < 0.01$) and connected ($\beta = 0.368$, $p < 0.01$). However, H1a is not supported as ASP was not associated with the consumer feeling more served ($\beta = 0.071$, $p > 0.05$). In addition, focusing on the moderating effects, which were calculated in a two-stage approach (e.g., Henseler and Chin, 2010), need for social interaction reinforced the relationship between ASP and feeling more connected ($\beta = 0.129$, $p < 0.01$), supporting the moderating effect proposed in H8d. In turn, the moderating effects of need for social interaction on the psychological tensions proposed in H8a ($\beta = 0.048$, $p > 0.01$), H8b ($\beta = 0.080$, $p > 0.05$) and H8c ($\beta = 0.08$, $p > 0.05$) were not supported. Finally, need for social interaction was associated with the consumer feeling less understood ($\beta = -0.144$, $p < 0.01$), empowered ($\beta = -0.213$, $p < 0.01$) and connected ($\beta = -0.200$, $p < 0.01$). In turn, need for social interaction was not related to feeling more served ($\beta = -0.068$, $p < 0.01$).

To better illustrate the interaction effects between ASP and need for social interaction on feeling more connected (vs. alienated), we followed Belanche et al.'s (2021b) approach, that is, comparing groups (see

Table 1
Construct Reliability, Convergent Validity, Discriminant Validity and Common Method Bias.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	A	CR	AVE	FVIF
ASP (1)	**0.946**	*0.139*	*0.074*	*0.283*	*0.288*	*0.387*	*0.405*	*0.550*	*0.476*	0.942	0.963	0.896	1.429
NSI (2)	−0.123	**0.904**	*0.070*	*0.175*	*0.242*	*0.245*	*0.128*	*0.191*	*0.243*	0.890	0.930	0.817	1.092
SvsE (3)	0.073	−0.073	N.A.	*0.421*	*0.332*	*0.314*	*0.232*	*0.219*	*0.277*	N.A.	N.A.	N.A.	1.296
UvsM (4)	0.275	−0.171	0.421	N.A.	*0.441*	*0.515*	*0.435*	*0.391*	*0.408*	N.A.	N.A.	N.A.	1.620
EvsR (5)	0.279	−0.239	0.332	0.441	N.A.	*0.535*	*0.298*	*0.376*	*0.440*	N.A.	N.A.	N.A.	1.588
CvsA (6)	0.377	−0.236	0.314	0.515	0.535	N.A.	*0.422*	*0.488*	*0.553*	N.A.	N.A.	N.A.	1.895
FV (7)	0.382	−0.121	0.224	0.421	0.290	0.409	**0.868**	*0.576*	*0.655*	0.934	0.948	0.753	1.638
SV (8)	0.502	−0.174	0.212	0.374	0.358	0.466	0.534	**0.875**	*0.729*	0.897	0.929	0.765	1.285
INT (9)	0.456	−0.228	0.272	0.402	0.433	0.545	0.624	0.686	**0.970**	0.969	0.980	0.941	2.118

Notes: ASP = Automated Social Presence, NSI = Need for Social Interaction, SvsE = Served vs. Exploited, UvsM = Understood vs. Misunderstood, EvsR = Empowered vs. Replaced, CvsA = Connected vs. Alienated, FV = Functional Value, SV = Social Value, INT = Intention to use, N.A. = not applicable, CR = Composite Reliability, AVE = Average Variance Extracted, FVIF = Full Variance Inflation Factor. Bold numbers on the diagonal show the square root of the average variance extracted; numbers below the diagonal represent inter- construct correlations; italic numbers above the diagonal represent heterotrait–monotrait values.

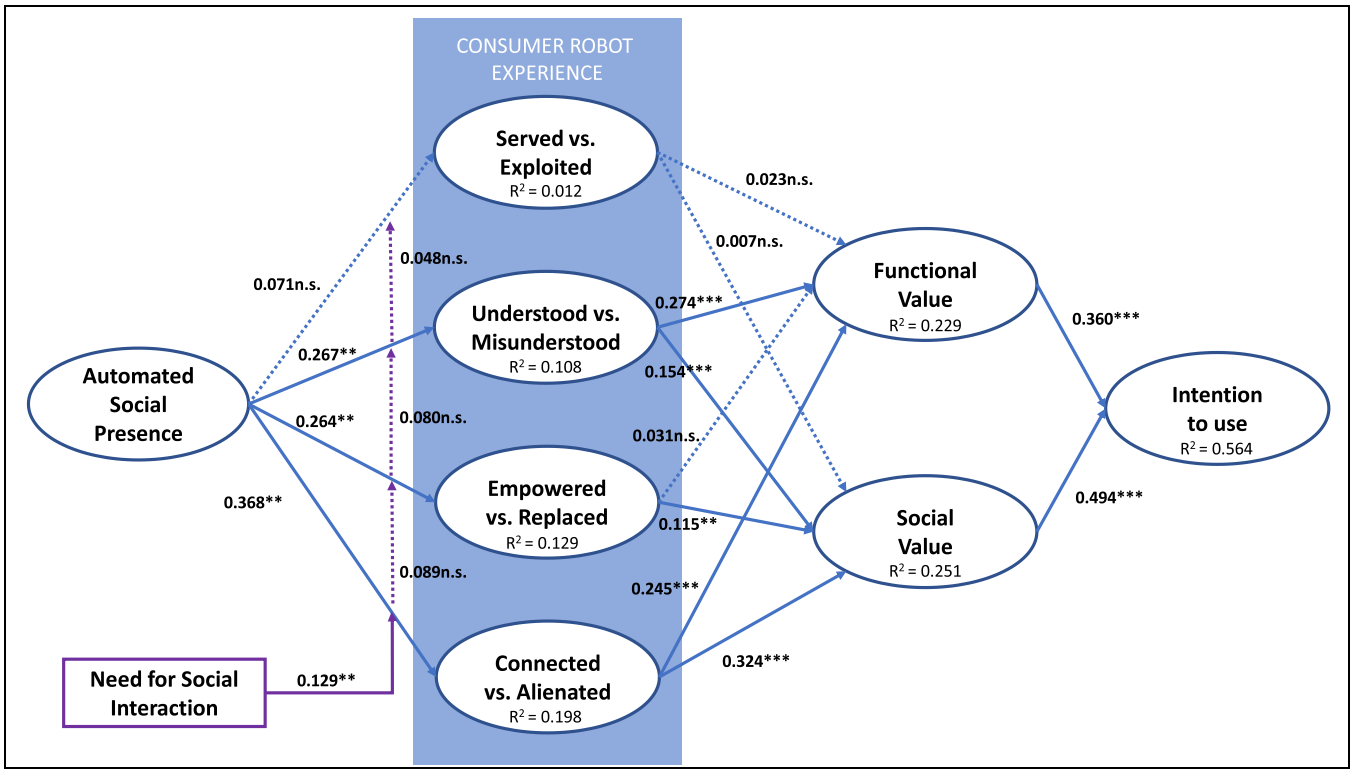

Fig. 2. Path estimates and significance Notes: Solid lines represent significant effects; dashed lines represent non-significant effects. ** Significant at the 0.01 level, * significant at the 0.05 level, n.s. non-significant.

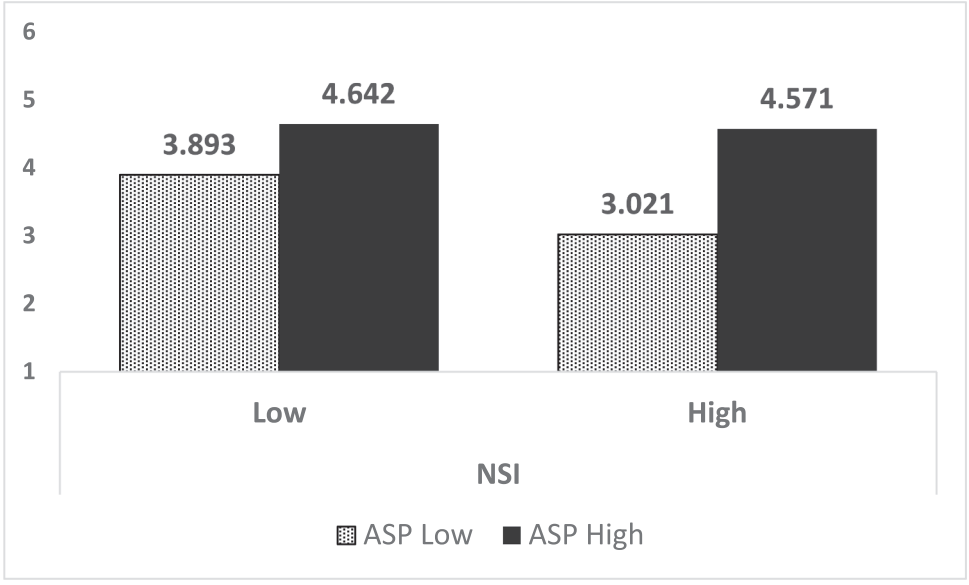

Fig. 3. Moderation effect of need for social interaction on consumer social experience with robots (feeling connected or alienated) Note: ASP = Automated Social Presence, NSI = Need for Social Interaction.

Fig. 3). Specifically, we divided consumers who reported high and low levels of ASP based on their mean scores on the ASP measure. Similarly, we distinguished between consumers with a high or low need for social interaction based on the mean of the reported scores. We observed that the difference in feeling more connected (vs. alienated) between those who reported a high ASP and those who reported a low ASP was greater among those with a higher need for social interaction.

In addition, the results indicated that listening experience does not affect perceived value. That is, feeling served does not affect either functional ($\beta = 0.023$, $p > 0.05$) or social value ($\beta = 0.007$, $p > 0.05$); thus, H2a and H2b are not supported. In turn, for classification experience, feeling understood was positively associated with both functional ($\beta = 0.274$, $p < 0.01$) and social value ($\beta = 0.154$, $p < 0.01$), thus, H3a and H3b are supported. As to delegation experience, while feeling empowered increased social value perceptions ($\beta = 0.115$, $p < 0.05$), it did not affect functional value ($\beta = 0.031$, $p > 0.05$), H4b supported, H4a not supported. Finally, social experience affected perceived value. Specifically, feeling connected had a positive association with both

functional ($\beta = 0.245$, $p < 0.01$) and social value ($\beta = 0.324$, $p < 0.01$), supporting H5a and H5b. Finally, as predicted, and in support of both H6 and H7, functional ($\beta = 0.360$, $p < 0.01$) and social value ($\beta = 0.494$, $p < 0.01$) were positively associated with intention to use service robots.

The proposed model allows us to partially predict our endogenous variables: served vs. exploited ($R^2 = 0.012$), understood vs. misunderstood ($R^2 = 0.108$), empowered vs. replaced ($R^2 = 0.129$), connected vs. alienated ($R^2 = 0.198$), functional value ($R^2 = 0.229$), social value ($R^2 = 0.251$) and intention to use ($R^2 = 0.564$).

Finally, we analyzed whether consumers' experiences with AI, and perceptions of functional and social value, mediate the influence of ASP on use intention, and whether functional and social value mediate the influence of consumers' AI experiences on intention to use. This was done by calculating the bias-corrected and accelerated confidence intervals of the mediating effects, using 10,000 subsamples, with no sign change (Chin, 2010; Zhao et al., 2010). Table 2 summarizes the indirect effects on intention to use. Specifically, ASP is indirectly associated with intention to use service robots via feeling connected and understood, and via functional and social value. Analogously, feeling connected and understood are indirectly associated with intention to use service robots via both functional and social value.

6. Discussion

In contrast to previous, mostly theoretical, examinations of ASP (van Doorn et al., 2017), this exploratory research investigates the impact of ASP on consumer well-being. For the first time in this research field, our study also empirically assesses the psychological tensions (Puntoni et al., 2021) evoked by service robot experiences in terms of the creation of functional and social value, given that these values increase the consumer's intention to use robots. Next, we discuss in detail the study's findings, which we compare with those in the previous literature (we also address associated concepts) to focus scholars' attention on related, emerging topics.

Table 2
Specific Indirect Effects.

Effects	Estimates	95 % bias-corrected and accelerated confidence interval
ASP → Served vs. Exploited → Functional Value → Intention to Use	0.001n.s.	(-0.002; 0.008)
ASP → Served vs. Exploited → Social Value → Intention to Use	0.000n.s.	(-0.003; 0.008)
ASP → Understood vs. Misunderstood → Functional Value → Intention to Use	0.020*	(0.004; 0.044)
ASP → Understood vs. Misunderstood → Social Value → Intention to Use	0.026*	(0.011; 0.050)
ASP → Empowered vs. Replaced → Functional Value → Intention to Use	0.003n.s.	(-0.007; 0.017)
ASP → Empowered vs. Replaced → Social Value → Intention to Use	0.015n.s.	(-0.000; 0.036)
ASP → Connected vs. Alienated → Functional Value → Intention to Use	0.033**	(0.014; 0.059)
ASP → Connected vs. Alienated → Social Value → Intention to Use	0.059**	(0.031; 0.095)
Served vs. Exploited → Functional Value → Intention to Use	0.008n.s.	(-0.035: 0.054)
Served vs. Exploited → Social Value → Intention to Use	0.003n.s.	(-0.053; 0.063)
Understood vs. Misunderstood → Functional Value → Intention to Use	0.098**	(0.053; 0.152)
Understood vs. Misunderstood → Social Value → Intention to Use	0.076*	(0.016: 0.137)
Empowered vs. Replaced → Functional Value → Intention to Use	0.011n.s.	(-0.029; 0.055)
Empowered vs. Replaced → Social Value → Intention to Use	0.057n.s.	(-0.001; 0.116)
Connected vs. Alienated → Functional Value → Intention to Use	0.088**	(0.041: 0.144)
Connected vs. Alienated → Social Value → Intention to Use	0.160**	(0.096; 0.229)

Notes: ** Significant at the 0.01 level, * significant at the 0.05 level, n.s.- non-significant.

Focusing on the psychological tensions resulting from consumers' interactions with service robots, our study found that classification experience is the most important, with higher perceptions of ASP increasing consumers feelings of being understood (over misunderstood). This finding suggests that ASP may be crucial for generating experiences in which robots make consumers feel understood, as they do when they interact with empathetic human employees who are able to adapt services to consumers' needs and preferences. Thus, higher ASP may make consumers feel that they are being treated as they deserve, which will provide greater functional and social value than interactions with less sophisticated technologies (Rust and Huang, 2021). It is likely that consumers will feel more stressed and misunderstood when dealing with technologies that lack ASP, for example, self-service machines that make them do work previously carried out by human employees, rather than being assisted by humanized, quasi-empathetic robots. Quasi-empathy belongs in the area of "artificial emotions", as human-to-robot (and human-to-human) encounters involve artificial emotions (Belk, 2022). Because a service robot will not be influenced by real emotions, it will, theoretically, reliably express artificial emotions in an effort to maximize human satisfaction. This area has been explored in the context of sex robots (Belk, 2022), perhaps the most intimate ASP-related relationship we can have, where consumers are not faced with mood swings or "not tonight" statements. Nonetheless, artificial love, empathy and emotions exist not only in the bedroom, but also in many service encounters where consumers demand that they be understood, an aspect that ASP may help to solve.

ASP can alleviate psychological tensions related to delegation experiences by making consumers feel empowered, rather than replaced. Thus, feeling that one is in the presence of a social entity (i.e., the service robot) may make consumers feel self-confident, rather than diminished, by the technology. Interestingly, feeling empowered increases social value, which suggests that consumers want to be seen in the eyes of others as powerful, rather than weak (including in their interactions with service robots). However, feeling empowered does not affect functional value (i.e., the reliability and quality of the service provided by the robot). This finding expands previous knowledge on humans' AI-based role stress, which was that employees experiencing displacement by AI see the technology as detrimental in both functional and social terms (Consiglio and van Osselaer, 2022; Loureiro et al., 2023; Lu et al., 2020). Nonetheless, in the interface between humans and AI-led machines, the line may blur, in both directions, such that we perceive machines to be like humans and humans to be like machines (Belk, 2017). When consumers are served by machine-like humans, such as people aided by an AI device, we may judge them as less human - and less admirable - than people not artificially enhanced (Castelo et al., 2019). Therefore, our results, put in context, suggest that consumers appreciate the benefits of a technology if it resembles, but not distorts, the human characteristics of service provision.

The results of the study also revealed that ASP makes consumers feel more connected, rather than alienated (social experience), and that this experience enhances both functional and social value perceptions. This is probably the most important finding of the research (as reinforced by the highly significant mediation analysis). This finding suggests that robots should be made more human-like, from the consumer's perspective, that is, more social (social role, social tasks, empathy, etc.), rather than more anthropomorphized, as often suggested by previous studies. This result concurs with the findings of previous studies about the advantages of incorporating social attributes into AI-based services (Pitardi and Marriott, 2021). It also bodes well for those who advocate the use of robot/chatbot companions for specific groups of consumers, such as the elderly (Englehart, 2021; Koutentakus et al., 2020; Lu et al., 2021). For instance, a recent *meta*-analysis confirmed that, as socially

assistive robotic technologies have matured, robots are being successfully introduced as complementary caregivers to patients with dementia to increase their activation and mitigate their depression (Lu et al., 2021). Interestingly, the use of pet robots as social assistive agents has been shown to improve patients' health, which suggests that ASP benefits may be linked not only to human-like robots, but also to animal-like robots.

In relation to social experience, the study found that the need for social interaction exerts a significant moderating effect on the influence of ASP on social experience. This finding is interesting because it shows that ASP's effect on consumerś feelings of being connected (rather than alienated) is stronger for those with higher needs for social interaction. This result is in line with the previous comments made about robotś social roles. After all, consumers want to connect with other people, and/or other social entities, because we are social by nature. The better these other entities play a social role, the better the consumer feels. For example, in the film *Cast Away*, Tom Hanks plays the role of a survivor who befriends an object – a volleyball named Wilson – as a substitute for other humans. This example shows how attached some people may become to non-sentient objects and brands, and how the attribution of social abilities to objects can help alleviate solitude. Thus, our findings suggest that there is demand for ASP in service encounters, at least on the part of some individuals, and that increasing consumers' perceptions of ASP in technologies could alleviate consumerś concerns about being alienated or isolated by the technologies.

The studýs results did not support the proposal that ASP affects AÍs listening capacity; similarly, the effects of listening capacity on functional and social value were not found to be significant. This finding suggests that ASP does not make users feel served or exploited, and contrasts with the results of previous research which suggested that listening capacity is important in some systems/contexts. For instance, voice assistants are mostly assessed based on their listening and responding capacities, and sometimes evoke privacy (and "creepiness") concerns (i.e., exploited) because consumers feel the devices are eavesdropping. For example, people say that they are exposed to advertisements based on conversations they have had at home (Guerreiro et al., 2022). On the same lines, recent research has suggested that ASP may lead consumers to feel discomfort in certain service encounters, due to AÍs listening capacity. In particular, consumers prefer to engage with robots (particularly robots scoring low in ASP) than with humans when they must disclose personal information (Konya-Baumbach et al., 2023), or in embarrassing service encounters (Pitardi et al., 2022; Holthöwer and van Doorn, 2023). Thus, it seems that AI's listening capacity is not detrimental per se, but it is the recording or misuse of private information which concerns consumers.

Finally, it was found that consumers who feel understood and connected derive more functional value from service robots (based on their perceptions of their efficiency and reliability). Analogously, consumers who feel understood, empowered and connected have increased social value perceptions, that is, they perceive they create positive impressions in other people and enjoy more social approval. The results of our study revealed that both functional and social value increase consumers' intentions to use robots in the future, a finding which corroborates previous postulates in the service value literature in both technological and non-technological contexts (c.f. Zeithaml et al., 2020).

6.1. Theoretical implications

Our study analyzes the impact of AI and service robots on consumers' well-being in a nascent research field, an area which differs from the more common research stream that examines the impact of social media on their well-being. As noted above, some initial insights into this issue were provided in a labor setting, where theoretical (e.g., Xiao and Kumar, 2021; Lu et al., 2020) and empirical studies (Beane, 2019; Loureiro et al., 2023) have already explored employees' role stressors when they encounter AI (e.g., disempowerment based on being substituted). Recent studies more specifically focused on consumers' subjective well-being (e.g. happiness, loneliness) found that, contrary to the intended consequences, AI friendship apps, such as those designed to foster AI-human relations, may be counterproductive, that is, they decrease consumers' welfare (Marriott and Pitardi, 2023). However, despite the value of these early investigations, little is known about the consequences of the introduction of AI in terms of consumers' feelings and well-being. To bridge this research gap, our research analyzed ASP and found it is a crucial element in shaping consumerś well-being and in service robot adoption.

In a key theoretical contribution, our research focuses on ASP, which we argue is a new variable, conceptually different from the widely investigated anthropomorphism (van Doorn et al., 2017; Blut et al., 2021). Our work expands the scant existing knowledge on ASP, an underexplored feature of AI and service robots. ASP differs from anthropomorphism in its conceptualization, epistemology and operationalization, thus, its impact on key marketing and consumer behavior variables deserves further attention. Our proposal advances the scarce empirical research into ASP by proposing and testing how it alleviates the four psychological tensions described in the consumer AI experience framework (Puntoni et al., 2021). Consistent with the scarce, and mostly theoretical, research into ASP (van Doorn et al., 2017; Holthöwer and van Doorn, 2023), our study revealed that in the robot waiter case, ASP is mostly beneficial because it helps alleviate three physiological tensions (i.e., classification, delegation and social; but not data capture experience), which leads to higher consumers' perceptions of functional and social value that, in turn, increase their intentions to use robots. Therefore, our research suggests that service robots with an increased level of ASP are perceived as having positive, human-like abilities that can help consumers feel understood, empowered and connected, which complements findings about the value of the human-like characteristics of robots in previous research (Belanche et al., 2021b, Ruiz-Equihua et al., 2023). That does not necessarily mean that robots should be made more anthropomorphic, but that consumers should feel they are in the presence of someone else, with the stress not on human-like, esthetic features, but on technological capacities that make them seem more human (social role, social tasks, empathy, etc.).

In addition, we distinguish between the functional and social value of service robots. Although functional value (efficiency, reliability) may be the more common and logical driver of consumers' intentions to use robots, we found that social value (i.e. being seen in a positive light by other people) also motivates consumers to use robots. This finding challenges the findings of previous studies which suggested that consumers do not positively appreciate the social value of robots (e.g. Belanche et al., 2021b), and aligns with the premises of a growing research stream which emphasizes the social benefits of using service robots in public contexts (e.g. in tourist attractions, Lin et al., 2023). In this regard, our study expands the knowledge of social value antecedents and consequences in the context of robot waiters and should encourage other scholars to assess the social approval/disapproval associated with using robots and AI in public (e.g. AI pictures in social media) and private contexts (e.g. AI appliances at home).

6.2. Implications for management and society

As outlined in the discussion, the findings of our study suggest that service providers should invest in increasing ASP. This may be carried out, as noted previously, by increasing the technology's anthropomorphism (by giving the robots/AI names, physical aspects, voice, etc.) and by increasing the technology's capabilities to include social skills and have it behave like a human or social entity (i.e., robot humanness, Belanche et al., 2021b). In particular, our study into robot waiters found that ASP significantly determines consumer classification, delegation and social robot experiences, these experiences being positively related to functional and social values and, therefore, to consumers' intentions to use robots in the medium and long term.

While technologies may not be able to "understand" consumers, in the fullest sense of the word, service providers should not design technologies that make consumers feel misunderstood. Customizing services to each individual to make him/her understood is a challenge that providers need to overcome. Nonetheless, the positivist and reductionist power of metrics and indexing may provide technology giants and governments with the illusion of precision and control, while actually creating and exacerbating problems of inequality and inequity (Beer, 2016; Day, 2014; Muller, 2018). Thus, an unanticipated and unintended consequence of the introduction of AI with advanced classification capabilities may be that the consumer suffers harm. For instance, in a sinister scenario, consumers may be "redlined" out of homes in areas due to de facto racial profiling (Noble, 2018; O'Neal, 2016); mortgages, school and university admissions, policing, court decisions and hiring decisions may all hang in the balance.

In relation to the delegation experience, service providers should find mechanisms to empower consumers such that they welcome the introduction of technologies rather than feel replaced. This aspect is particularly important in labor settings, where automation is seen by employees as a threat and a role stressor (Xiao and Kumar, 2021; Lu et al., 2020); this view is sometimes shared by consumers who foresee a world where human tasks are no longer carried out by humans. This finding can also be linked to the new phenomenon of ChatGPT, which is being introduced into internal and frontline operations by many firms. Some employees and consumers feel empowered by it, and others feel replaced; however, this feeling seems to be more important from a social image approach than in terms of behavioral effect. Alternatively, rather than using AI to improve their own productivity, many companies are using AI to encourage consumers to produce free content. Nonetheless, what marketers call co-creation, critics are apt to regard as cooptation or "prosumption" (Ritzer and Jurgenson, 2010). These companies solicit content, which attracts eyeballs to the (mislabeled) "Sharing Economy", which is not about sharing at all (Belk et al., 2019). In other words, Facebook, YouTube, WeChat and other giant social media platforms can be argued to be profiting from the consumer's labor (Zwick et al., 2008).

From a consumer social experience approach, our study clearly showed that ASP alleviates the consumer's feelings of alienation. Therefore, higher investment in ASP would help technologies engage consumers socially and make them feel socially connected. However, as an unintended consequence, alleviating this psychological tension may make consumers feel more solitary because they recognize they are using the technology as a substitute for social relations. Indeed, given the increasing solitude of people in current society, some institutions, such as the European Commission (2018, p. 19), have stated that the relational conception of human dignity should be characterized by social (human) relations; that is, "autonomous systems must not interfere" with the rights to have "meaningful human contacts" and "to establish and develop relationships with other human beings." This might be extended beyond human beings. AI-led devices might be increasingly present in social interactions in the immediate future. Rust and Huang (2021) suggested that AI and robotics first helped humanity in the physical economy, for example, in automated robotic factories. Next, they contributed to the thinking economy, for example, with ChatGPT4 and Dalle-2. Today, AI and robotics are part of the feeling economy, for example, sex dolls that can converse and use bio feedback to enhance human orgasms (Belk, 2022). Humans can still distinguish artificial emotions from "real" emotions but, as with chatbot speech (Belk, 2023), the gap is closing.

Although our study found that ASP had no significant effect on feeling served or exploited, previous evidence suggests that AI with listening capacity may cause consumers discomfort when sensitive information must be disclosed (Holthöwer and van Doorn, 2023; Konya-Baumbach et al., 2023). However, in other contexts, service robots have not generated negative perceptions in the consumer of being listened to, or exploited, because, taking chatbots as an example, they have to be invited by the user to provide help, rather than being an imposition. This is the case, for instance, with mental therapy bots, such as Woebot, and friendship and self-knowledge facilitating chatbots, such as Replika (Belk, 2023). In these cases, the the contributions made by the technologies based on what people have said in the past are not likely to be perceived as creepy.

7. Limitations and further research

To empirically analyze ASP and the psychological tensions associated with consumerś robot experiences, this exploratory research studied a single service robot waiter. Further research might analyze other service robots which produce both very high and low levels of ASP. The results of examinations into psychological tensions may also vary based on service type (e.g., chatbots and sex robots), which suggests that context specific studies should be carried out. It would be particularly interesting to study the psychological tensions evoked by AI-based services that lack a humanoid physical appearance (e.g., algorithms, speaker voice assistants), and to explore alternative variables that may affect consumerś psychological tensions. Future research might develop more precise scales to measure the four dimensions of the consumer's robot experience and their associated psychological tensions.

Another limitation is that our work proposes that functional and social value are the two most important indicators of service value, following previous literature that suggested that these factors are more affected by robot anthropomorphism, and reflect robotś competence and warmth, respectively (Belanche et al., 2021b). Nevertheless, the relationships between service value perceptions could be more complex, given that the psycho-cognitive constructs in consumer behavior research tend to be interrelated. Further research might analyze the impact of psychological tensions on the economic and hedonic value of services provided by robots. Cultural and personal factors may also play an important role in increasing/reducing psychological tensions. Indeed, recent research has suggested that some aspects of technology readiness (e.g., technological discomfort) may encourage rather than discourage robot use, because some technologies can help consumers avoid the learning normally needed to use complex machines/systems (Flavián et al., 2022). Similarly, the work does not take into account previous consumer experience with service robots but, due to its important role in the adoption of AI-based services (Flavián et al., 2022), future research might examine how previous consumer experience may influence psychological tensions and service value perceptions.

Although beyond the scope of the present study, the aforementioned concerns suggest that further research should take place into the ethical aspects of technology introduction into services. An open letter signed by thousands of AI researchers, CEOs and other well-known people linked to the development of AI warned "AI labs [are] locked in an out-of-control race to develop and deploy ever more powerful digital minds that no one – not even their creators – can understand, predict, or reliably control" (Future of Life Institute, 2023). We predict that this race among companies for AI and automation development will not stop. Thus, we encourage scholars to compensate for the lack of reflection in the industry about the impact of the introduction of these technologies into people's lives by increasing scientific research in the area.

CRediT authorship contribution statement

Carlos Flavián: Writing – review & editing, Supervision, Project administration, Conceptualization. **Russell W. Belk:** Writing – review & editing, Supervision, Conceptualization. **Daniel Belanche:** Writing – original draft, Investigation, Data curation, Conceptualization. **Luis V. Casaló:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

1 Measurement scales.

Scale items
Automated Social Presence (adapted from van Doorn et al., 2017; Lin et al., 2021)
Interacting with this service robot would make me feel as if I were interacting with a human-being.
Interacting with this service robot would make me feel a sense of human contact.
Interacting with this service robot would not make me imagine it was a living entity.
Interacting with this service robot would give me have the impression that it has feelings.
Need for Social Interaction (adapted from Dabholkar and Bagozzi, 2002)
Human contact in services provision 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.
It bothers me to use a machine when I could talk to a person instead.
Listening experience: served vs. exploited (developed based on the proposals of Puntoni et al., 2021)
Using this service robot would make me feel… from "1″ exploited to "7" served.
Classification experience: understood vs. misunderstood (developed based on the proposals of Puntoni et al., 2021)
Using this service robot would make me feel… from "1″ misunderstood to "7" understood.
Delegation experience: empowered vs. replaced (developed based on the proposals of Puntoni et al., 2021)
Using this service robot would make me feel… from "1″ empowered to "7" replaced.
Social experience: connected vs. alienated (developed based on the proposals of Puntoni et al., 2021)
Using this service robot would make me feel… from "1″ connected to "7" alienated.
Functional Value (adapted from Yang and Jolly, 2009; Sweeney and Soutar, 2001)
I think that the robot-based service would be reliable
I think that the robot-based service would function well
I think that the robot-based service would be well delivered
I think that the robot-based service would provide in a timely manner
I think that the robot-based service would fulfill my needs well
I think that the robot-based service would offer consistent quality
Social Value (adapted from Yang and Jolly, 2009; Sweeney and Soutar, 2001)
Using the robot service would make me feel accepted by others
Using the robot service would make a good impression on other people
Using the robot service would give me social approval
Using the robot service would improve the way I am perceived by others
Intention to use (adapted from Belanche et al., 2021b)
Given the chance, I intend to use this kind of service robot
I would like to use this service robot in the future
I expect to use this service robot in the future

Notes: All scales used seven-point Likert-type response formats, from 1 ("completely disagree") to 7 ("completely agree"), except as noted. Item in italics was eliminated in the validation process.

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