Social robot-delivered customer-facing services: an assessment of the experience

Santiago Forgas-Coll, Ruben Huertas-Garcia, Antonio Andriella, Guillem Alenyà

***Abstract*—The ability to install social intelligence protocols in robots in order for them to exhibit conversational skills has made them ideal tools for delivering services with a high cognitive and low emotional load. Little is known about how this capability influences the customer experience and the intention to continue receiving these services. Experiences were assessed in a study simulating customer-facing service delivery, and the constructs of the technology readiness index and stated gender were analysed as possible moderators in a quasi-experiment. Hedonic quality was the most relevant factor explaining attitude, and attitude explained intention to use as well as social influence. As for the constructs of technological readiness and gender, optimism and innovativeness seem to be the most likely candidates for moderating the other variables. The most optimistic and the most innovative route would be for the main actors to continue adapting to social robot technology in the future.**

***Index Terms*—Customer-facing service, social robot, social intelligence protocols, experience, technology readiness index, sex.**

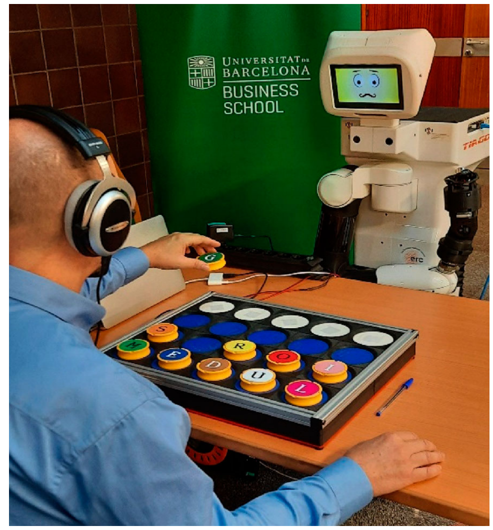

Fig. 1. Participant playing a cognitive game with the assistance of the robot.

I. Introduction

In recent years, the use of devices that employ artificial intelligence (AI) to deliver frontline services has boomed, partially due to the belief that they improve the customer experience (Crolic et al., 2022; Lu et al., 2020) while reducing the cost of service delivery (Belanche et al. 2021; Mende et al., 2019). The outbreak of the COVID-19 pandemic and the consequent lockdown and social distancing measures have also contributed to its acceleration. From the very beginning of the pandemic, there was a vast increase in the use of chatbots to improve customer service (Ameen, 2021), self-service machines in stations and airports (Lien et al., 2021) and social robots in services previously provided by people (Aymerich-Franch, 2020) Chiang Trimi, 2020). Of all these robotic solutions, this study focuses on humanoid social robots, for which major growth is expected. In fact, the Social Robots Market which was estimated at USD 1.77 Bn. in 2020, is expected to reach USD 13.77 Bn. by 2027, registering a compound annual growth rate (CAGR) of 34.06% between 2021 and 2027 (MMR, 2022).

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Social robots are programmable machines equipped with AI software that allows them both to act autonomously during service delivery and also to exhibit social skills during human-robot interaction (HRI), thanks to complementary devices (cameras and other sensors) and social intelligence protocols (Breazeal et al., 2016; Forgas-Coll et al., 2022a). Moreover, robots that display human-like forms seem to be the most suitable for the delivery of frontline services (Belanche et al. 2020a; Lv et al., 2022) as they convey the feeling that customers are interacting with another social agent (Van Doorn et al., 2017). Such characteristics have led to an increase in the application of social robots in various industries, where they are replacing human employees in hotel and restaurant receptions, schools, supermarkets, nursing homes and hospitals, among others (Belanche et al. 2021; Blaurock et al., 2022).

However, there are doubts as to whether the rate at which social robots are being deployed in frontline services will be the same after the pandemic, or will instead slow down. While some authors (Belanche et al. 2020b, Lu et al., 2020; Mende et al., 2019) expect the trend to continue, arguing that their deployment helps to improve customer service and reduce its costs, others have their doubts (Blaurock et al., 2022), as not all social robots are equipped with the same levels of intelligence (Huang and Rust, 2018). In this respect, the best-equipped models, featuring automation autonomy, are laboratory prototypes or entail high production costs (e.g. SOPHIA),

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while those that are sold at more affordable prices are pre-programmed devices that, despite conveying the feeling of autonomy, are actually scripted with predefined responses (e.g. Pepper or non-humanoid JIBO) (Robert et al., 2020). In other words, there are doubts as to the real capacity of current robotic equipment to deliver services and they are in danger of becoming merely decorative items (Andriella et al. 2022a).

In their implementation of frontline social robots, service companies must consider the convergence of three factors: the specific characteristics of the service encounter (type of delivery, degree of provider involvement and duration); the profile of the consumer requesting the service and, finally, the type of robot (human-like) and equipment (software) needed to deliver the service (Belanche et al. 2020a; Lv et al., 2022).

However, several observations have emerged from the literature review. First, the application of social robots to services is an emerging field of research and has led to a proliferation of theoretical proposals, but there is still a lack of empirical studies on specific applications (Belanche et al. 2020a; Čaić et al., 2018; Flavian and Casaló, 2021; Huang and Rust, 2018; van Doorn et al., 2017; Wirtz et al., 2018). Second, the literature includes studies conducted in different fields, such as education, healthcare (Conti et al., 2017; Turja et al., 2020), retail (De Gauquier et al. 2021; Rancati and Maggioni 2022) and hospitality (Schepers et al., 2022; Tuomi et al., 2021). However, while most describe the physical appearance of the robot (human-like), very few specify the degree of intelligence (software) with which it is equipped. Recent work has proposed that social robots can exhibit different types of AI: mechanical, analytical, intuitive and empathetic (Huang and Rust, 2021) and, furthermore, certain empirical studies have estimated the degree of perceived importance of this AI (Belanche et al. 2020b; Schepers et al., 2022), but do not make it clear whether such intelligence is pre-programmed or generated with automation autonomy (Robert et al., 2020). Third, very few studies on frontline services have analysed direct experiences with social robots, as most scenarios are hypothetical (e.g. written descriptions, pictures or videos) (Belanche et al., 2020b). Exceptions include De Gauquier et al. (2021), Forgas-Coll et al. (2022a), Rancati and Maggioni (2022) and Tuomi et al. (2021). Fourth, although social robots are becoming more common in the world (Shourmasti et al., 2021), implying a greater number of touch points (Lemon and Verhoef, 2016), their study still takes technology-acceptance approaches, even in long-term experiments such as Cesta et al. (2016), rather than direct measures of experience, which would be a better reflection of the emerging reality (Lemon and Verhoef, 2016; Williams et al., 2020). Finally, most HRI studies about services apply a homogenous approach to customers. However, given the diversity of goals and expectations expressed by different customer groups, it would be advisable to analyse the market by segments (Schepers et al., 2022).

This research aims to address the above-mentioned gaps and in doing so makes the following contributions. First, it is among the first studies to empirically examine a robot that is pre-programmed to perform a specific frontline service task (see Fig. 1). Second, through qualitative research, we attempt to simplify the swarm of models used in the literature to explain intention-to-use by proposing a parsimonious model consisting of three main drivers of such experiences (pragmatic quality, hedonic quality, social influence), a mediator (attitude) and a general output (intention-to-use). Third, the moderating role that the factors of Technology Readiness (optimism, innovativeness, discomfort and insecurity) and stated sex might play in explaining this parsimonious model of experience is analysed.

II. Conceptual Framework

The physical appearance of social robots is one of the most studied topics in the literature (Belanche, 2021; Walters et al., 2008), where it is highlighted that humanoid forms are preferred over zoomorphic and mechanical-looking ones (Blaurock et al., 2022). Although robot designs that appear more human-like (Brackeen, 2017; Lv et al., 2022) and mimic human-to-human behaviour and conversation (Luff et al., 2014) are currently predominant, little is known about the technologies applied to reproduce these behaviours (Lee et al., 2017). While robots with automation autonomy technology can react independently to each user's questions or answers (Goertzel, et al., 2017), those with pre-programmed technology follow scripts with a set number of answers that are always the same regardless of the human reaction (Robert et al., 2020). Since the former are much more expensive than the latter, and considering that users do not notice their lack of autonomy in short-term interactions, the deployment and application of pre-programmed robots still makes sense (Forgas-Coll et al., 2022b; Tuomi et al., 2021). Below, we describe the design process of social intelligence protocols in pre-programmed robots.

A. *Social intelligence protocols in pre-programmed social robotics*

A feature that differentiates service delivery by social robots from traditional self-service technologies (ATMs, boarding pass kiosks, vending machines, etc.) is the ability to socially engage with consumers (Van Doorn et al., 2017; Mende et al., 2019). This is possible because social robots incorporate social intelligence protocols that allow them to simulate a conversation during HRI (Forgas-Coll et al., 2022a).

Social intelligence protocols are made up of several components, including activation, facial recognition and communication protocols. The latter are a set of rules and processes that enable communication between two agents or systems, whether technological, robotic or human (Bochmann and Sunshine, 1980). For example, if we consider a conversation between people, the communication protocol is made up of three elements: what is said, how it is said, and the characteristics of who it is said to (Brennan and Hanna, 2009). If this protocol is transferred to an HRI, what is said is pre-programmed in the so-called ”script”, and how it is said is determined by the text-to-speech software, which can also be combined with non-verbal language signals (Chidambaram et al., 2012; Forgas-Coll et al., 2022a). However, the process of the third element – knowing the characteristics of the audience – is more complex, and requires clear expectations about their level of knowledge of the topic or their ability to understand what is being said (Brennan and Hanna, 2009).

When social intelligence protocols (such as communication) do their job properly, even in the case of chatbots such as Amazon's Alexa, consumers come to perceive that they are interacting with a similar agent to themselves (Hoy, 2018), and this perception generates greater trust when it comes to exchanging information (Bickmore, 2005) Waytz and Norton, 2014). In the case of social robots, the deployment of this ability means consumers find them less intimidating and more trustworthy (Lyons et al., 2021) and thus achieve friendlier interactions with them (Złotowski et al., 2015). Robotics designers also programme movements, such as facial expressions, to generate natural communication and give the sensation of conveying feelings (Broekens, 2007).

In short, the combination of verbal messages together with non-verbal signals (e.g. different gestures and eye expressions) helps to foster HRI (Van Pinxteren et al., 2019) and makes the non-human entity appear more familiar, explainable and predictable (Epley et al., 2007). Indeed, evidence has been collected that shows that users treat robots as human beings without being aware of it (Eyssel et al., 2011). Both physical appearance and conversational skills in robots, therefore, help to create an endearing experience when interacting with them (Złotowski et al., 2015).

However, although much progress has been made in the development of social intelligence protocols, they are not yet able to deliver verbal and non-verbal signals in the form of an understandable, natural conversation over a sustained period of time (Andriella et al. 2022a). For instance, chatbots are not expected to reach credible levels of human intelligence before 2029 (Shridhar, 2017). However, one way to improve the perceived performance of social robots is for designers to make greater consideration of users' own skills in relation to the corresponding task, and also their ability and predisposition with regard to HRIs, this being the third element of the communication protocol (Brennan and Hanna, 2009). Evidence has been found in the literature that the context, task and target audience condition the effectiveness of communication protocols. For example, in the context of a nursing home for the elderly, a communication protocol that makes one robot assistant playful was perceived as more engaging and intelligent than the serious one, whereas the serious one was considered less anxiety-provoking and less creepy than the playful one (Sundar et al., 2017). In a healthcare context, an experiment was designed consisting of hypothetical scenarios, depicted in vignettes, where helpful robot behaviours were created that were more focused on conversing with patients than on the task, and the results showed that the patient-centred (vs. task-centred) robot was perceived as an agent with higher emotional intelligence, trustworthiness and acceptability (Chita-Tegmark et al., 2019). In short, the context and the target audience condition the type of anthropomorphic design and, in turn, the social intelligence protocol that is considered most appropriate.

B. The experience of the service delivered by a social robot

According to Pine and Gilmore (1998), any company's main objective is to create memorable events, and the memory of the 'experience' becomes the product that customers consume. Later studies have proposed more refined definitions. For example, De Keyser et al. (2015, p. 14) described it as "comprised of the cognitive, emotional, physical, sensory, and social elements that mark the customer's direct or indirect interaction with a (set of) market actor(s)". This definition, which has been replicated numerous times, highlights the interactive, multidimensional nature of the 'experience' construct (Lemon and Verhoef, 2016; Williams et al., 2020). The interactive nature implies that the experience arises from an interaction between a customer and a set of market actors through various interfaces, both human (e.g. frontline employees) and non-human (e.g. self-service technologies or robots) (De Keyser et al., 2015). Moreover, it is a necessary factor, as without interaction there is simply no experience (Pollio et al., 1997). Therefore, social robots, thanks to their ability to generate social interaction during the customer encounter, can co-create these memorable experiences (Wirtz et al., 2018). The co-creative view of experience, introduced by Prahalad and Ramaswamy (2004), proposes that customers should play an active role and not simply be passive observers, since they should participate in shaping their own experience.

The first studies to assess HRI experiences as service providers were conducted considering technology acceptance models within a wide range of services and scenarios (as shown in Appendix A). Among services, Hospitality and Tourism, Education, Elderly Care and Healthcare have been highlighted (Blaurock et al., 2022). However, few studies have used this construct to assess the experience of interacting with social robots and most are highly partial analyses of certain components (a review of the literature can be found in Shourmasti et al., 2021).

Several models have been proposed to try to explain the factors that make up the consumption experience. One of the most popular is that of Klaus and Maklan (2013), who presented an approach consisting of four dimensions: product experience, outcome focus, moments of truth, and peace of mind. However, some of its precedents, such as "product experience", are difficult to fit into a service delivery experience offered by a social robot. Furthermore, as Gupta (2016) pointed out, a more comprehensive and widely accepted scale of experience still needs to be developed, and Lemon and Verhoef (2016) called for this to be short and comprehensive. This study proposes a parsimonious model deduced from qualitative research and made up of three basic precedents (pragmatic quality, hedonic quality and social influence), a mediator (attitude) and, as the final output, the intention to continue using the service.

Although experience is a multidimensional construct, it has been theoretically suggested that its hedonic and utilitarian components shape consumer attitude (Batra et al. 1991) De Keyser et al., 2015). In fact, Voss et al. (2003) operationalised customer attitude derived from experience as a two-dimensional construct consisting of a hedonic dimension, resulting from the sensations derived from its use, and a utilitarian dimension derived from the functions it performs. Also, in the field of new technologies (smartphones, tablets, chatbots, robots, etc.), two dimensions have been considered to explain the experience: goal-oriented qualities (utilitarian) and qualities derived from the use thereof being interesting and stimulating (hedonic) (Rogers et al., 2011; Schrepp et al., 2017). It was also suggested by Kuehnl et al. (2019) that the utilitarian and hedonic dichotomy actually involves two different constructs.

There are several approaches to the output generated by the hedonic and utilitarian components. On the one hand, some consider the output to be satisfaction (Klaus Maklan, 2013; Williams et al., 2020), although other authors have found a stronger link with relative satisfaction (Aksoy et al. 2017) or even with attitude (Hofmeyr et al., 2008). In this study, attitude has been considered as a partial output, since it is one of the most widely used constructs both in the evaluation of the consumption of traditional products and services, and in that of those linked to new technologies (Batra et al. 1991, Davis et al., 1989; Voss et al., 2003). Based on the above arguments, the following hypotheses are proposed:

- **H1.** The perceived functional quality of service delivery by a social robot is positively related to attitude.
- **H2.** The perceived hedonic quality of service delivery by a social robot is positively related to attitude.

Although the hedonic and utilitarian dimensions are still considered in the form of qualities as the basis of experience, new dimensions are being considered (Lemon and Verhoef, 2016). Klaus and Maklan (2013) proposed that, in addition to functional and emotional factors, the evaluation of experience should include peer influence. In other words, social influence, which is part of De Keyser et al.'s (2015) definition of experience. For example, it is considered that the mere presence of another person and their emotional state can expand the consumer's experience, especially when it comes to people that they consider relevant (Echterhoff et al., 2009).

Regarding the overall outcome, previous studies on self-service technologies have considered both intentions to use and quality of service as outputs (Verhoef et al., 2009). This study has opted for intention to use, which is common in models of technology acceptance (Davis et al., 1989) and social robotics (Forgas-Coll et al., 2022b). Based on the above arguments, the following hypothesis is proposed:

- **H3.** The perceived social influence of a service delivery by a social robot is positively related to the intention to use it.

Finally, as is common in technology acceptance models (Davis et al., 1989), attitude relates utilitarian and hedonic antecedents to the final output. Thus, the following hypothesis is proposed:

- **H4.** The perceived attitude towards the delivery of a service by a social robot is positively related to intention to use it.

C. Technological readiness as a moderation and market segmentation criterion

Each discrete event generates a distinct experience for each consumer (Speer et al., 2007), which has been demonstrated in previous literature by showing that individuals' reactions and their degree of technological acceptance of robotic equipment are heterogeneous (Forgas-Coll et al., 2022a). Therefore, when designing events, service companies try to delineate them for specific segments, based on certain customer characteristics that represent the archetype of the target market (De Keyser et al., 2015). These archetypes are usually formed based on factors that are considered moderators and are often likely to be used as segmentation criteria (Wedel and Kamakura, 2000).

To determine these characteristics, or factors, this study has followed Hayes' (2018, p. 78) recommendation to try to "[answer] questions about when or for whom is the domain of moderation analysis". Among the "for whom" responses in an HRI context, Mende et al. (2019) proposed the use of measures linked to familiarity or degree of expertise, such as technological readiness (Parasuraman and Colby, 2015), which is a fairly common factor in the study of AI consumption (e.g. Flavián et al., 2022; Mende et al., 2019; van Doorn et al., 2017).

In general, some users of new technological devices find positive feelings aroused, while in others they are negative (Parasuraman and Colby, 2015). Parasuraman (2000, p. 308) defined technological readiness as "people's propensity to adopt and use new technologies to achieve goals in home life and work". He also considered that it must have a multidimensional structure formed by two motivators (degree of optimism and self-perception of the degree of innovativeness) and two inhibitors (degree of discomfort and perceived insecurity with new technologies) (Parasuraman and Colby, 2015). In addition, previous research has already reported the independence of these four dimensions, whereby each of them measures different aspects of a person's degree of openness and perceived difficulty with new technologies (Lu et al., 2012).

Although previous studies have used technological readiness as an indirect antecedent for consumer satisfaction, for example, in a study of e-commerce in China (Lu et al., 2012) or regarding the intention to use robotic financial advisors (Flavián et al., 2022), this study intends to explore the four dimensions as moderating factors and, therefore, susceptible to be used as segmentation criteria (Wedel and Kamakura, 2000). Although one of the outcomes of exploratory research is to gather evidence in order to formulate hypotheses, the research can be better framed by proposing a priori working hypotheses that can later be readjusted (Casula et al., 2021). These working hypotheses are as follows:

- **WH1.** The two motivators (degree of optimism and self-perceived degree of innovativeness) will be more suitable criteria for moderating the experience of being served by a social robot than the two inhibitors (degree of discomfort and perceived insecurity with new technologies)

D. Stated sex as a moderator and as a market segmentation criterion

Another factor that often plays a moderating role in the adoption of new technologies, including social robots, is declared sex (usually labelled gender) (e.g. Chawla and Joshi, 2020; Flavián et al., 2022; Forgas-Coll et al., 2022b). It is currently common to differentiate between biological sex (observable in nature) and gender identity (a more nuanced concept that refers to a self-attributed variable) when considering market segmentation (Nickel et al., 2020). Traditionally, biological sex has been a basic factor in market segmentation, product design (e.g. clothing and apparel) and the scripting of communication and advertising campaigns (Meyers-Levy and Loken, 2015). However, as the conceptualisation of sex and gender becomes more fluid (Butler, 2006; Fausto-Sterling, 2001), gender identity is becoming more influential in the marketing of products and services (Nickel et al., 2020).

The main reason for using biological sex as a segmentation criterion is the selectivity hypothesis (Moss, 2009). According to this premise, the fact that men and women respond to different stimuli in commercial images, and in the shapes of product designs, is because the two sexes have a predisposition to process information differently (Meyers-Levy and Loken, 2015; Nickel et al., 2020). It has been determined that women are more inclined to process stimuli captured by the senses, particularly sight, in a joint and comprehensive manner, whereas men tend to process stimuli selectively, focusing their attention on certain specific elements and basing their overall assessment on them (Darley and Smith, 1995). This is also reflected in the appreciation of new technologies (He and Freeman, 2019), and in the evaluation of HRI with social robots (Forgas-Coll et al., 2022b).

Recent findings propose the existence of a relationship between at least two ways of processing information gathered from stimuli and the most appropriate criterion for segmentation, namely either biological sex or gender identity (Nickel et al., 2020). That is, while the innate abilities to process stimuli derived from biological sex tend to result in different visceral, subconscious and rapid responses, when important personal and socially significant gender identity is considered, responses to stimuli tend to be more reflexive, conscious and militant (Nickel et al., 2020; Stets and Burke, 2000). Therefore, when considering shopping experiences for convenience products or service delivery with little customer involvement, it is more appropriate to use biological sex as a criterion for segmentation. However, when considering shopping experiences for special products or high-involvement services that may contribute to identity formation or status signalling, segmentation by gender identity would be more appropriate.

In this study, which considers a service experience provided by a social robot, but with little customer involvement, we expect participants whose stated sex is male to show greater willingness to be served than those whose stated sex is female. Therefore, the working hypothesis will be:

- **WH2.** Declared sex will be appropriate as a moderator and as a market segmentation criterion

III. Methodology

A multi-method approach was used to select the main drivers of experience, test the parsimonious model hypotheses and explore the moderating role of technological readiness and declared sex (see Fig.2) First, exploratory qualitative research was conducted in which thirteen participants shared a service

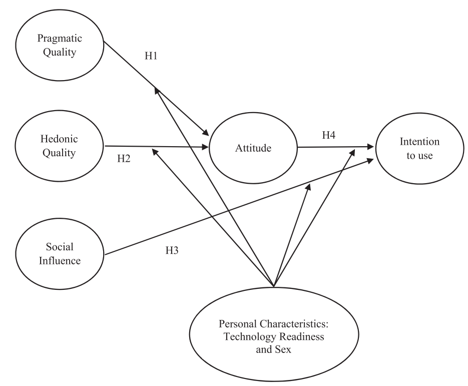

Fig. 2. Proposed model.

prototype experience with a TIAGo robot, which was pre-programmed to assist with the task, and featured a social intelligence protocol (Andriella et al, 2020; Andriella et al., 2022a). This was followed by quantitative research, where the experience was replicated with 272 participants in a field study.

A. Qualitative study

To provide suitable settings for the service encounter with robots, a service prototype was designed. During the design process of new products or services, it is common to test prototypes in an early service experience before the final launch (Polaine et al., 2013; Tuomi et al., 2021). A service prototype is a model that collects the essential characteristics of a service provided in the real world and is used to explore different tangible and intangible aspects, as well as the reactions of different stakeholders, with the aim of improving the design (Oh et al., 2013; Razek et al., 2018; Tuomi et al., 2021). Simulations are used when the evaluation of the real-life marketing policy might be too complicated, time-consuming or prohibitively expensive (Tkachenko et al., 2016). Furthermore, Wolfe and Roberts (1993) pointed out that these simulation exercises can produce similar results to those of field experiments, that is, they achieve similar external validity.

1) Procedure and apparatus: To simulate the service prototype, a task was created with the essential elements in terms of time, help requirements and robot attention, and which consisted of a board game where the player had to form the five-letter name of a Nobel laureate from 10 letter tiles with the help of a TIAGo robot. The following elements of this game were taken into account: i) it reproduces a sequence of steps with the risk of getting stuck, as is common in complex ATM transactions (Meuter et al., 2005); ii) the duration of the experience (about five minutes) is very similar to that of a hotel check-in (Solichin et al., 2019) and to the duration of other experiments (Tuomi et al., 2021); and, iii) hints and messages of empathy and reassurance are common in customer-facing services (Kim et al., 2016).

The participants were assisted in the task by a pre-programmed TIAGo robot, a semi-humanoid mobile manipulator with a height of 110 cm, a weight of 70 kg and a diameter of 54 cm. It combines perception, navigation, manipulation and human-robot interaction skills (PAL Robotics, 2022).

To enable the robot to perform the task, game movements, a social intelligence protocol (a script called SOCIABLE) (Andriella et al., 2022a) and coordination with non-verbal language facial expressions were programmed (Chidambaram et al., 2012). Loquendo text-to-speech software was used to produce speech and the robot's head was replaced with an LCD screen to show facial expressions (see Fig .1).

Once the participant had sat down to start the task, the robot was switched on. After a few words of welcome, TIAGo provided a brief explanation of the game and the type of help that it was going to provide. Next, the second group of routines with hints and help was activated: If the player was slow to move the tile, the robot gave a hint (”I will give you a clue, look right”); if s/he took the right tile, it gave encouraging messages (”Wow, you found it”); if s/he took the wrong tile, messages of doubt (”Are you sure?”); if s/he made the wrong move, messages of reassurance (”No worries, that happens sometimes”); between moves, backchannel messages (”humm”); and finally, when completing the game, farewell messages (”It has been a pleasure playing with you, hope you enjoyed it too”).

2) Data collection: For the first qualitative research, a sample of potential consumers was invited by email following a similar approach to Patton's (1990) intensity sampling, i.e. focusing on the characteristics of users who in previous studies (Forgas-Coll et al. 2022c) expressed more opposing views towards the use of social robots as service providers (extreme age cohorts and stated sex). In total, 13 participants (8 reporting to be female (F) and 5 male (M)) between 18 and 65 years of age were recruited (including 5 young people from 18-25 and 4 older people from 58-65). The sample size was determined by the saturation or redundancy criterion, i.e. the sample was terminated when no new information was received from newly sampled units (Lincoln and Guba, 1985).

All participants were invited individually to partake in the experience of performing a task with the help of a humanoid robot in the IRI (Institute of Robotics and Industrial Informatics CSIC-UPC) laboratory. Once there, and after a brief introduction to the study, the participants were invited to play a board game with the help of the TIAGo robot. Although none reported previous experience with this game or interacting with a social robot, they all completed the task. Moreover, no critical incidents were observed, in the sense that none of them got stuck at any point. After the interaction (average duration: 5 minutes and 40 seconds), one of the researchers invited them into an adjacent room and asked them to comment on any unobserved critical incidents, and then conducted a semi-structured interview (Veling and McGinn, 2021). After asking for the participants' permission, their responses were recorded. None of them received any kind of remuneration. The questions were: What elements of the experience do you consider to have been important in your interaction with the robot, and, furthermore, could you specify which of these elements were most positive and which were a barrier to your appreciation of a vivid experience with the robot? In particular, the researchers were interested in understanding the motivations behind their appraisals of the experience of receiving a brief service from a social robot.

3) Data analysis: The qualitative data was analysed in the form of conventional content analysis (Hsieh and Shannon, 2019). First, the participants' explanations were listened to and transcribed, highlighting interesting paragraphs, which were assigned to 40 unique codes. These were grouped into second-level codes that, in turn, were grouped into third-level codes. This axial coding process resulted in eight bolds grouped into two labels (Hsieh and Shannon, 2019; Tuomi et al., 2021): “Robot-agent related experiences” (robot shape, facial gestures and tone of voice) and “Frontline service experience” (functional skills, hedonics, social influence, attitude change, and intention to use). To verify that the eight bolds and two labels adequately captured the participants' views, two of them were asked to rate a draft of the hierarchical coding process. They both felt that the eight themes adequately reflected their views. Finally, to ensure analytical consistency, the codebook and descriptions of each main theme, together with interview excerpts, were sent to two independent reviewers (Coder 1: F 35 years, Business Administration graduate; Coder 2: M 58 years, Electronic Engineer) for re-coding. Following Tuomi et al. (2021), inter-coder reliability was determined by Cohen's Kappa estimation and, in both cases, indicated good agreement (¿.60) (Landis and Koch, 1977). However, for the quantitative research, only the five bolds grouped under the label “Frontline service experience” were considered.

4) Findings: In general, the participants rated the experience of being assisted by the TIAGo robot positively. However, almost all of them spontaneously commented on aspects related to the robot's shape, facial gestures, and tone of voice, where there was some discrepancy. Regarding shape, the younger respondents were inclined towards a more human-like robot, while the older ones preferred a mechanical-looking shape:

”I didn't like its physical appearance, as it didn't inspire confidence from the outset” (F 18 years).

”If it looked more human it would be more approachable” (F 22 years).

”I thought he looked nice”, and ”I wouldn't like him to look more human” (F 58 years).

”I like the fact that he looks like a robot and not like a person” (M 61 years).

Disagreement is also expressed with regard to facial gestures:

”The facial changes are very inexpressive” (F 26 years).

”I liked the fact that the facial expression changed depending on the conversation” (F 23 years).

Although there is a certain consensus regarding the importance of the voice (”I think the voice is the most important aspect” F 65 years) and a preference for female voices (”I like the female tone of voice” F 26 years, and ”the lady's tone of voice is pleasant” M 58 years), there is no consensus regarding the tone:

”The robot's voice is very cold” (F 23 years), and ”the volume of the sound is a bit irritating” (F 22 years).

”The tone of voice is very pleasant and makes the robot friendly” (F 58 years).

Concerning the thematic analysis of the experience of a frontline service encounter with a humanoid service robot, five

TABLE I
DEMOGRAPHIC PROFILE OF THE RESPONDENTS

Variable and Cases (%) and Variable and Cases (%)
Gender and and **Nationality** and
Male and 136 (50) and Spanish and 224 (82.3)
Female and 136 (50) and Rest of Europe and 10 (3.8)
Age and and South American and 17 (6.6)
18-24 years and 211 (77.6) and Asian and 13 (4.8)
25-34 years and 37 (13.6) and Others and 8 (3.2)
35-44 years and 7 (2.6) and and
45-54 years and 7 (2.6) and and
More than 54 years and 10 (3.7) and and

main themes emerged:

1) Functional skills, suitability and ability of the TIAGo robot to help complete the task. The suitability of the social robot to provide a frontline service based on offering effective information or guidance was highlighted ("it is clear and quick to offer help" F 22 years), although some areas for improvement were also mentioned:
   "It helped me, but I found it unintelligent" (F 58 years) or "when giving the clues, it could have talked about the colours of the tiles, which would have helped more" (F 26 years).
2) Hedonic skills. There was some consensus regarding the robot's ability to make the experience interesting and entertaining:
   "The experience was fun, and it didn't put me in a bad mood" (F 45 years).
3) Social influence. There was a discrepancy between generations regarding the manifest desire to tell family and friends about the experience:
   "It'll be amazing to tell friends about it" (F 23 years).
   "Although my impression was positive, if I tell them, they'll think I'm a bit crazy" (F 65 years).
4) Change in attitude. There was a certain consensus regarding a change to their previous assessment after the experience:
   "At first, I was a bit apprehensive about playing the game with the robot, but when you see it and start playing, you realise that it's harmless" (M 58 years).
5) Intention to use. There is a certain consensus regarding the stated desire to continue sharing experiences with the robot, although this is something that would happen in the long term.
   "I've never done anything like this before. I understood everything and so I wouldn't mind doing it another day" (F 26 years), and
   "I think today's experience was incredible, but it strikes me as very far removed from today's reality" (F 23 years).

B. Quantitative study

The second study, of a quantitative nature, takes the main factors derived from the first one, and establishes a causal relationship between them, as described above in the analysis of the experience of receiving a service from a humanoid social robot. This part also explores whether the moderating variables of technological readiness and declared sex might be segmentation criteria in this market. To this end, the simulation of the service generated in the qualitative study was replicated in a larger environment outside the laboratory.

1) Procedure and data collection: For the fieldwork, a stand was set up on the university campus of one of the largest universities in Spain. The stand consisted of two spaces: one was open to attract passers-by, and the other one was more private and contained the board game and a TIAGo robot. Passers-by were invited to play a game that replicated the service prototype. After they had agreed to take part, the volunteers received brief instructions, began to play the board game and, once finished, they filled in a questionnaire to evaluate the experience and provide their socio-demographic data. All participants stated that it was their first HRI experience and all of them completed the game. Although the 272 participants were controlled for sex, the sample was spontaneously skewed towards younger participants, hence it was a convenience sample. Table I shows the demographic data of the participants.

2) Measurement instrument and analytical procedure: To measure the constructs of the parsimonious model of the participants' experience, scales from previous literature were used (Table 2 shows the constructs and items). Specifically, for the Pragmatic and Hedonic Quality constructs, the Short Version of the User Experience Questionnaire (UEQ-S) (Schrepp et al., 2017) consisting of four seven-point differential semantics for each construct (e.g. Confusing/Clear; Inefficient/Efficient; Complicated/Easy; Obstructive/Supportive) was used. For Attitude, the Heerink et al. (2010) scale consisting of three five-point items was used. For the other two constructs, social influence and intention to use, three five-point items from previous literature were employed (Forgas-Coll et al., 2022b).

The Technological Readiness Index (TRI) proposed by Parasuraman and Colby (2015) was used to test that factor, which is made up of 16 seven-point items (four per construct) to measure customers' levels of optimism, innovativeness, discomfort and insecurity (Table 4, describes the constructs and items of each). Finally, three possibilities were offered for the stated sex: male, female or other.

Structural Equation Modelling (SEM), based on variance and covariance matrices by maximum likelihood with EQS 6.4 (Bentler, 2006), was used to assess the psychometric characteristics of the scales, adjust the model and test the proposed hypotheses. But, for the exploratory analysis of the quasi-experiment, five scenarios (four consisting of the four constructs of technological readiness and, the fifth, declared sex) were adjusted by Ordinary Least Squares (OLS) (Hayes, 2018).

3) Scale validation: Before testing the model, the psychometric characteristics of the constructs that make up the parsimonious model for estimating experience and TRI were analysed. Since the questionnaires were answered with a researcher available to settle any doubts, none were returned incomplete.

From the confirmatory factor analysis (CFA) of the parsimonious model, one of the items of the Hedonic Quality scale was eliminated, leaving three items, and, from the TRI scale,

TABLE II
ANALYSIS OF THE DIMENSIONALITY, RELIABILITY AND VALIDITY OF THE SCALES (MEAN AND SD)

and Factor loading and Mean (SD)		
Pragmatic Quality (AVE: 0.55; CR: 0.78; C. Alpha: 0.77)		
Confusing/Clear	0.58***	1.71 (1.45)
Inefficient/Efficient	0.64***	1.24 (1.76)
Complicated/Easy	0.74***	1.38 (1.59)
Obstructive/Supportive	0.77***	0.91 (1.57)
Hedonic Quality (AVE: 0.57; CR: 0.75; C. Alpha: 0.75)		
Boring/Exciting	0.74***	0.74 (1.43)
Not interesting/Interesting	0.77***	1.25 (1.47)
Usual/Cutting edge	0.62***	1.01 (1.21)
Social influence (AVE: 0.63; CR: 0.80; C. Alpha: 0.80)		
I think my friends would like me to use the robot	0.68***	2.98 (1.07)
I think it would give a good impression if I played with the robot	0.86***	3.17 (1.09)
I think that people whose opinion I value would look favourably upon me playing with the robot	0.74***	3.35 (1.13)
Attitude (AVE: 0.71; CR: 0.86; C. Alpha: 0.86)		
I think it is a good idea to use the robot	0.84***	3.63 (0.92)
I find the robot interesting	0.80***	3.94 (0.95)
I consider it correct to use the robot	0.82***	3.78 (0.95)
Intention to use (AVE: 0.59; CR: 0.77; C. Alpha: 0.77)		
If the robot were available, I would try to use it	0.81***	3.40 (1.13)
If the robot were available, I would try to use it whenever I could in my spare time	0.75***	2.74 (1.21)
If the robot were available, I would sometimes think about when I could use it	0.60***	2.20 (1.07)

Note: the model fits Chi-square (χ^2): 95.8532; df: 90; p: 0.31682; RMSEA: 0.015; CFI: 0.996; NNFI: 0.995
AVE is the average variance extracted, CR is the composite reliability. *p ¡ 0.05; **p ¡ 0.01; ***p ¡ 0.001

TABLE III
DISCRIMINANT VALIDITY OF THE SCALES

	Pragmatic Quality	Hedonic Quality	Social Influence	Attitude	Intention to Use
Pragmatic Quality	0.74				
Hedonic Quality	0.55***	0.76			
Social Influence	0.25***	0.49**	0.80		
Attitude	0.38***	0.56***	0.51***	0.84	
Intention to Use	0.19*	0.58***	0.55***	0.69***	0.77

Below the diagonal: correlation estimated between the factors.
Diagonal (bold figures): square root of AVE.
*p ¡ 0.05; **p ¡ 0.01; ***p ¡ 0.001

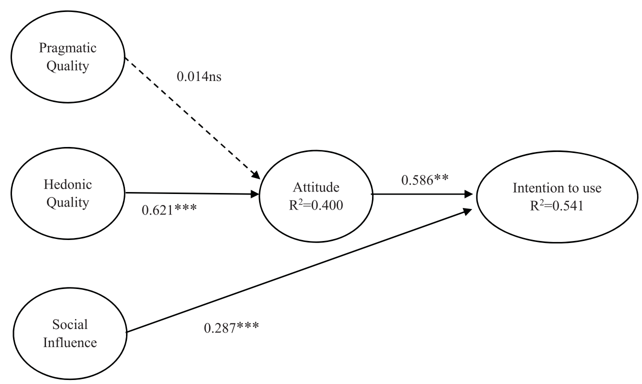

Fig. 3. General structural model results (**p ¡ 0.01; ***p ¡ 0.001).

three of the 16 items were eliminated, leaving the constructs Optimism, Discomfort and Insecurity with three items, which is the minimum number per construct to identify a SEM model (Baumgartner et al. 1996). The dimensionality, reliability and construct validity measures of the parsimonious experience model are shown in Table II. All Cronbach's alpha values are above 0.75, and those of the average variance extracted (AVE) are above 0.55 for all constructs, indicating good reliability (Fornell and Larcker, 1981). Almost all factor loadings exceeded 0.6 (the only exception was the Confusing/Clear item, with a loading of 0.58) and t-values were significantly high in accordance with the literature (Hair et al., 2010). The AVEs were also higher than the squared correlations for all pairs of constructs, thereby supporting discriminant validity (Table III). Measures of dimensionality, reliability and validity of the TRI scale are shown in Table IV. All Cronbach's alphas reached values above 0.8 and all AVEs were above 0.65. All factor loadings exceeded 0.7 and t-values were significantly high (Hair et al., 2010). Its discriminant validity, as reported in Table V, was also confirmed (Fornell and Larcker, 1981).

4) Results of the structural model: The parsimonious model for evaluating the experience was fitted using SEM by maximum likelihood with EQS 6.4 (Bentler, 2006) and the results are shown in Table VI and Figure **??**. The respective goodness-of-fit R2 values were 0.400 for attitude and 0.541 for intention to use. Hence, they have acceptably high values for the sample size, indicating good predictive power (Hayes, 2018).

The results supported three of the four hypotheses. They indicated that the perception of pragmatic quality after receiving the service from the robot did not affect attitude ($\beta = 0.014$, n.s.) and, therefore, Hypothesis 1 is not supported. Conversely, hedonic quality is a relevant antecedent of attitude ($\beta = 0.621, p < 0.001$), supporting Hypothesis 2. As expected, perceived social influence had a positive and significant influence on intention to use ($\beta = 0.287, p < 0.001$), supporting Hypothesis 3, and finally, attitude had a positive and significant impact on intention to use ($\beta = 0.586, p < 0.01$), supporting Hypothesis 4.

5) Scenario results: Once the model had been tested, the working hypotheses were explored to determine whether some TRI constructs or declared sex could be moderators. For this purpose, the scales of each of the TRI constructs

TABLE IV
ANALYSIS OF THE DIMENSIONALITY, RELIABILITY VALIDITY OF THE TECHNOLOGY READINESS SCALE (MEAN AND SD)

	Factor loading	Mean (SD)
Optimism (AVE: 0.70; CR: 0.86; C. Alpha: 0.85)		
New technologies contribute to a better quality of life	0.71***	4.28 (0.72)
Technology gives me more freedom of mobility	0.77***	4.14 (0.81)
Technology makes me more productive in my personal life	0.97***	4.18 (0.80)
Innovativeness (AVE: 0.65; CR: 0.85; C. Alpha: 0.85)		
Other people come to me for advice on new technologies	0.75*	2.86 (1.12)
In general, I am among the first in my circle of friends to acquire new technology when it appears	0.79*	2.33 (1.00)
I can usually figure out new high-tech products and services without help from others	0.77*	3.43 (1.08)
I keep up with the latest technological developments in my areas of interest	0.77*	3.02 (1.15)
Discomfort (AVE: 0.73; CR: 0.87; C. Alpha: 0.87)		
Technical support lines are not helpful because they do not explain things in terms I understand	0.92***	2.99 (1.04)
I sometimes think that technology systems are not designed for use by ordinary people	0.74***	3.15 (0.90)
There is no such thing as a manual for a high-tech product or service that is written in plain language	0.83***	2.85 (0.94)
Insecurity (AVE: 0.68; CR: 0.84; C. Alpha: 0.83)		
People are too dependent on technology to do things for themselves	0.70***	3.65 (1.01)
Too much technology distracts people to a point that is harmful	0.71***	3.86 (0.98)
Technology lowers the quality of relationships by reducing personal interaction	0.98***	3.81 (0.96)

Note: The model fits Chi-square (χ^2): 66.1579; df: 55; p: 0.14412; RMSEA: 0.027; CFI: 0.992; NNFI: 0.989
AVE is the average variance extracted, CR is the composite reliability.
$*p < 0.05; **p < 0.01; ***p < 0.001$

TABLE V
DISCRIMINANT VALIDITY OF THE TR SCALE

	Optimism	Innovativeness	Discomfort	Insecurity
Optimism	**0.84**			
Innovativeness	0.26	**0.81**		
Discomfort	0.11	0.06**	**0.86**	
Insecurity	-0.11	0.01	0.08	**0.82**

Below the diagonal: correlation estimated between the factors.
Diagonal (bold figures): square root of AVE.
*p <0.05; **p <0.01; ***p <0.001

TABLE VI
CAUSAL RELATIONS IN THE GENERAL MODEL

Independent variable	Dependent variable	β	T	R^2
Pragmatic Quality	Attitude	0.014	0.15	0.400
Hedonic Quality		0.621***	5.71	
Social Influence	Intention to use	0.287***	9.32	0.541
Attitude		0.586**	2.74	

Significant at *p <0.05; **p <0.01; ***p <0.001

(optimism, innovativeness, discomfort and insecurity) were estimated and, based on the scores, the sample was divided into two subsamples according to their median (high and low scores). In the case of sex, we simply selected those who declared themselves male or female. For each subsample, the parsimonious model for estimating experience was fitted using OLS. The results of the ten models: Low vs. High Optimism, Low vs. High Innovativeness, Low vs. High Discomfort, Low vs. High Insecurity, and Male vs. Female are shown in Tables VII to IX.

Starting with the motivators, we compared the results for Low vs. High Optimism (results in Table VII), showing that the Low model has a 9.8% better goodness-of-fit for intention to use than the High model ($R^2_Low - R^2_High = 0.098$). This difference could be considered an estimator of the size of the moderation effect between the less and the more optimistic (Hayes, 2018). Regarding the constructs that have reached significant values in the two paired models, on the one hand, the Highly Optimistic participants attached greater importance to both pragmatic quality ($\beta = 0.178, p < 0.05$) and hedonic quality ($\beta = 0.441, p < 0.001$), while the Low Optimists only assigned significant value to hedonic quality ($\beta = 0.383, p < 0.001$), to explain attitude. On the other hand, the Low Optimists attributed greater importance to social influence ($\beta = 0.326, p < 0.001$) and attitude ($\beta = 0.402, p < 0.001$) than the High Optimists ($\beta = 0.234, p < 0.01; \beta = 0.383, p < 0.001$) in describing their intention to use.

Regarding the comparison between Low vs. High Innovativeness (shown in Table VII), the results show that the Low group explains 12% better goodness-of-fit than the High one in the intention to use the service provided by a robot ($R^2_Low - R^2_High = 0.120$). Regarding the weight of the drivers, the High Innovativeness group assigned greater importance to hedonic quality ($\beta = 0.366, p < 0.001$) than to pragmatic quality ($\beta = 0.172, p < 0.05$), but it was the Low group that assigned a higher hedonic value ($\beta = 0.454, p < 0.001$), although with only one driver to explain the attitude. Regarding the intention to use, the High Innovativeness group attributed greater importance to social influence ($\beta = 0.363, p < 0.001$) than the Low one ($\beta = 0.213, p < 0.01$), but it was the Low Innovativeness group that attributed greater importance to attitude ($\beta = 0.495, p < 0.001$) than High ($\beta = 0.286, p < 0.01$).

Regarding the inhibitors, the comparative analysis between Low vs. High is shown in Table VIII. In the case of discomfort, the goodness of fit of the Low group explained a little more, 2.7% ($R^2_Low - R^2_High = 0.027$), than the High one in intention to use. On the one hand, this shows that the High Discomfort group attached greater importance to pragmatic quality ($\beta = 0.163, p < 0.05$) than the Low Discomfort group and, furthermore, that the latter assigned greater weight to hedonic quality ($\beta = 0.491, p < 0.001$) than the former ($\beta = 0.357, p < 0.001$) to explain attitude. However, in the case of intention to use, the Low Discomfort group attributed more importance to social influence ($\beta = 0.316, p < 0.001$) and somewhat less to attitude ($\beta = 0.394, p < 0.001$) than the

TABLE VII
CAUSAL RELATIONS **OPTIMISM** AND **INNOVATIVENESS** FACTORS

		Optimism						Innovativeness					
		Low			High			Low			High		
Independent variable	Dependent variable	β	T	R^2	β	T	R^2	β	T	R^2	β	T	R^2
Pragmatic Quality	Attitude	0.069	0.81	0.291	0.178*	2.10	0.161	0.122	1.51	0.247	0.172*	1.98	0.220
Hedonic Quality		0.383***	4.51		0.441***	5.20		0.454***	5.61		0.366***	4.13	
Social Influence	Intention to use	0.326***	4.42	0.368	0.234**	2.79	0.270	0.213**	2.64	0.394	0.363***	4.72	0.274
Attitude		0.402***	5.45		0.383***	4.56		0.495***	6.13		0.286***	3.71	

Significant at *p <0.05; **p <0.01; ***p <0.001

TABLE VIII
CAUSAL RELATIONS **DISCOMFORT INSECURITY** FACTORS

		Discomfort						Insecurity					
		Low			High			Low			High		
Independent variable	Dependent variable	β	T	R^2	β	T	R^2	β	T	R^2	β	T	R^2
Pragmatic Quality	Attitude	0.082	1.01	0.276	0.163*	1.85	0.191	0.115	1.36	0.336	0.135	1.61	0.156
Hedonic Quality		0.491***	6.06		0.357***	4.05		0.528***	6.29		0.330***	3.94	
Social Influence	Intention to use	0.316***	4.31	0.339	0.253**	2.99	0.312	0.320***	3.87	0.323	0.265***	3.53	0.337
Attitude		0.394***	5.38		0.399***	4.71		0.370***	4.48		0.416***	5.54	

Significant at *p <0.05; **p <0.01; ***p <0.001

TABLE IX
CAUSAL RELATIONS **SEX**

		Male			Female		
Independent variable	Dependent variable	β	T	R^2	β	T	R^2
Pragmatic Quality	Attitude	0.116*	2.27	0.288	0.068	1.10	0.224
Hedonic Quality		0.276***	5.22		0.356***	4.98	
Social Influence	Intention to use	0.299***	4.01	0.349	0.288***	3.30	0.328
Attitude		0.514***	5.73		0.403***	4.39	

Significant at *p <0.05; **p <0.01; ***p <0.001

High Discomfort group ($\beta = 0.253, p < 0.01; \beta = 0.399, p < 0.001$).

As for the comparative analysis of Low vs. High Insecurity (results in Table VIII), the comparison shows that the Low group explained slightly more than 2.1% more of the goodness of fit than the High one ($R_L^2ow - R_H^2igh = 0.021$) in intention to use. Regarding the explanatory constructs of attitude, low insecurity participants attached greater importance to hedonic quality ($\beta = 0.528, p < 0.001$) than High ones ($\beta = 0.330, p < 0.001$). However, with respect to intention to use, it was Low Insecurity respondents who attributed greater importance to social influence ($\beta = 0.320, p < 0.001$) and somewhat less to attitude ($\beta = 0.370, p < 0.001$) than High Insecurity respondents ($\beta = 0.265, p < 0.001; \beta = 0.416, p < 0.001$).

Finally, the comparison by declared sex (Male vs. Female) is reported in Table IX. In this case the goodness of fit of the Male model explains slightly more than 2.1% more than the Female one ($R_L^2ow - R_H^2igh = 0.021$) for intention to use. Regarding drivers, males assigned greater importance to pragmatic quality ($\beta = 0.116, p < 0.05$) and less to hedonic quality ($\beta = 0.276, p < 0.001$) than females ($\beta = 0.356, p < 0.001$), who only valued the latter driver significantly in explaining attitude. Regarding intention to use, males attached greater importance to social influence ($\beta = 0.299, p < 0.001$) and attitude ($\beta = 0.514, p < 0.001$) than females ($\beta = 0.288, p < 0.001; \beta = 0.403, p < 0.001$).

In summary, on the one hand, in line with what was proposed in WH1, the motivational profiles (Innovativeness and Optimism) are the ones that most point to the existence of a moderating effect. On the other hand, stated sex does not seem to be a moderating criterion, contrary to WH2.

IV. DISCUSSION AND CONCLUSIONS

This study has considered a frontline service delivery prototype performed by a social robot that is pre-programmed for problem-solving AI and social intelligence protocols, and which offers the possibility of an early experience before its final launch (Polaine et al., 2013; Razek et al., 2018). Knowledge of customers' reactions to these experiences is much needed, as the consequences are still unclear (Schepers et al., 2022).

Although the concurrence of different actors (social robot and customers) usually leads to joint co-creation of value (Čaić et al., 2018), not all customers are as willing as others. The qualitative part of this research highlighted differences in the preferences of young and old participants regarding the shape of the robot (young people preferred it to be more human-like and older people more mechanical-looking). In the quantitative research, younger people were more willing to participate, and in the exploratory analysis to detect moderating variables, the two TRI motivators (degree of Innovation and Optimism), in line with what was proposed by WH1, were the best candidates.

A. Theoretical Implications

As a contribution of this research, the main drivers of a novel experience have been qualitatively described and a parsimonious model has been proposed (Lemon and Verhoef, 2016). However, as consumers become more experienced in interacting with social robots, their assessments are expected to become more sophisticated (Gupta, 2016). Nevertheless, after testing the parsimonious model, hedonic quality, referring to the most exciting and cutting-edge elements, emerged as the most relevant driver to explain changes in attitude, while pragmatic quality had no influence. This result is particularly interesting because, although the main function of the robot assistant was to help customers to complete a task that was as complex in its sequencing as some ATM transactions are (Meuter et al., 2005), this function has not been valued highly enough. Although early HRI studies emphasised the importance of utilitarian over hedonic factors (Heerink et al., 2010), later work highlighted the ability to entertain (De Graaf et al., 2019; Gamecho et al., 2015). Moreover, attitude continues to be the main driver explaining intention to use, as well as the social influence or perception that others have of it (Heerink et al., 2010; Forgas-Coll et al., 2022b).

Regarding the exploratory study on the moderating effect of the TRI scale (Parasuraman and Colby, 2015), only the motivators (degrees of innovativeness and optimism) and none of the inhibitors (discomfort and technological insecurity) obtained results that might suggest they should be considered as possible moderators (Hayes, 2018). In the case of the degree of optimism, the most optimistic customers, in addition to valuing hedonic quality, also value pragmatic quality. As for the most innovative, although they also value pragmatic as well as hedonic quality as drivers of attitude formation, this attitude does not translate into such strong intentions as there are among the least innovative. Hence, while the role of the social robot is appreciated by the more innovative participants, the change in attitude generated by the hedonic quality becomes more influential on the intention to continue using the robot's services among the less innovative. In short, the most optimistic and innovative users who appreciate the full benefits of the robot can be expected to be the main actors that will continue to adapt to social robot technology in the future.

Finally, despite evidence in the literature that sex plays a moderating role, in this study the differences between self-reported males and females are unremarkable and do not suggest the existence of such a role. The study thus contradicts previous findings that men report a higher propensity to use new technologies and interact with service robots than women (He and Freeman, 2019; Forgas-Coll et al., 2022b), or that women report lower levels of self-efficacy when dealing with new technologies (Sun and Zhang, 2006).

B. Managerial Implications

The introduction of social robots to frontline services represents a major challenge for managers, as it has both advantages and disadvantages. Obviously, the service provided by a social robot should be tested before its introduction, either as a prototype (Tuomi et al., 2021) or as a pilot test (Byrd et al., 2021) and not only to detect possible errors (Belanche, 2020b) but also to test the AI algorithms and their learning processes (Andriella, 2022b).

Consumers are quick to identify the robot as an agent of the company and hold the latter responsible for the outcome of the experience (Belanche, 2020b). Consequently, companies should use the successful outcomes of service encounters (no participant abandoned the task without completing it, despite the qualitative research indicating that ”the game is difficult” (F 23 years)”) both to communicate to their target audience that the social robot is being introduced to improve the service and, furthermore, that it is part of the organisation's commitment to technological innovation. If such communication does not occur (Byrd et al., 2021), it could lead users to perceive social robots more as toys or pets for entertainment purposes (Sabelli and Kanda, 2016) than as reliable providers of customer service. Furthermore, the results of this study indicate that robots equipped with social intelligence protocols are mostly accepted as providers of emotional support (Waytz and Norton, 2014), as opposed to the suggestion in the literature that they are more accepted when they replace employees in cognitive tasks (Wirtz et al., 2018).

C. Limitations and future research lines

As usual in academic research, this study contains certain limitations that may open up opportunities for future research. In the qualitative research, the debate about robot shape emerged spontaneously, with younger people favouring more human-like models and older people preferring them to be more mechanical-looking. This certainly opens up opportunities for cohort-based analysis of the service experience delivered by robots (Belanche, 2020a; Lv et al., 2022).

This study has tested a prototype service provided by a social robot with the essential elements for a service that offers some cognitive load and little affective load (Wirtz et al., 2018). The experience was also assessed using a parsimonious model, following Lemon and Verhoef's (2016) recommendation to propose short and complete models. As users become more familiar with such experiences, more sophisticated models can be expected. Therefore, longitudinal studies are needed that can help explain how variables evolve over time.

While the study was open for anyone to participate, the biggest response was from younger people, which somewhat skewed the sample. This differing predisposition between younger and older people to interact with a social robot highlights the need for more in-depth studies on the motivations and attitudes of diverse age groups.

Although the TIAGo robot helps the customer to perform a difficult task, the main explanatory driver of attitude change was hedonic quality, which may lead to the robot being perceived not as a substitute for a service worker but as a toy (Sabelli and Kanda, 2016). According to Byrd et al. (2021), there may be a gap in the company's communication, which opens up possibilities to investigate whether prior communication to consumers about the abilities of social robots is necessary before implementation.

Furthermore, the study has explored whether the possible constructs of TRI and reported sex could play a moderating role and thus be used as segmentation criteria (Wedel and Kamakura, 2000). Consequently, further research is needed to confirm the moderating influence of technological readiness components and sex on the adoption of services provided by social robots.

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APPENDIX
MAIN STUDIES MEASURING THE TECHNOLOGY ACCEPTANCE OF SOCIAL ROBOTS

Representative Articles	**Robot Used**	**Factors Involved**	**Significative Results**
Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010).	iCat, video RoboCar, Steffie virtual screen character	Antecedents: P.Adaptivity, Anxiety, Social presence, Sociability. Mediators: Usefulness, Ease of use Enjoyment,Trust, Attitude, Social Influence, Facilitating Conditions. Outcomes: Intention to Use, Use	Perceived Usefulness, Attitude, Perceived Ease of Use, Social Influence, Perceived Enjoyment –>Intention to Use; Social Influence, Perceived Adaptivity, Anxiety –>Attitude; Perceived Adaptivity, Perceived Ease of Use –>Perceived Usefulness; Perceived Enjoyment, Anxiety –>Perceived Ease of Use; Perceived Sociability, Social Presence –>Perceived Enjoyment; Attitude –>Trust; Trust –>Perceived Sociability; Perceived Sociability –>Social Presence
Shin, D-H., & Choo, H. (2011)	Three unnamed robots	Antecedents: Perceived adaptivity, Perceived sociability, Social presence. Mediators: Attitude, Perceived usefulness, Perceived Enjoyment. Moderators: Social Presence. Outcomes: Intention	Attitude, Perceived usefulness, Perceived Enjoyment, Social presence –>Intention; Perceived usefulness, Perceived Enjoyment, Perceived sociability, Perceived adaptivity –>Attitude; Perceived sociability –>Perceived Enjoyment; Perceived adaptivity –>Perceived usefulness. Moderating effects by social presence: P.usefulness, P. Enjoyment, P. sociability, P. adaptativity –>Attitude; P. sociability –>P. enjoyment; P. adaptivity –>P. usefulness
De Graaf, M. M., & Allouch, S. B. (2013)	NAO Humanoid Robot	Antecedents: Intelligence, Realism, Enjoyment, Robot Related Experience, Anthropomorphism, Age, Gender, Nationality. Mediators: Use Intention, Use Acttitude, Usefulness, Ease of Use, Enjoyment, Companionship, Social influence, Robot Related Experiences, Perceived Behavioral Control, Attitude Towards Robots, Gender, Adaptability, Anthropomorphism, Personal Innovativeness, Age, Sociability, Anxiety towards Robots, Attractiveness, Sociability, Image, Nationality. Outcomes: Use	Enjoyment –>Use; Use Attitude, Companionship, Adaptability, Perceived Behavioral Control –>Use Intention; Usefulness, Enjoyment, Sociability –>Use Attitude; Adaptability –>Usefulness; Perceived Behavioral Control, Anxiety towards Robots –>Ease of Use; Sociability –>Adaptability; Realism –>Intelligence; Adaptability, Attractiveness –>Enjoyment; Anthropomorphism –>Attractiveness; Sociability, Nationality –>Anthropomorphism; Anthropomorphism –>Realism; Realism, Intelligence, Nationality –>Sociability; Anthropomorphism –>Companionship; Age –>Social influence; Enjoyment –>Perceived Behavioral Control; Attitudes towards Robots –>Anxiety towards Robots; Anthropomorphism –>Attitude towards Robots
De Graaf, M.M., Allouch, S.B., & van Dijk, J.A.G.M. (2019)	No specific robot. Overview of a social robot and its uses.	Antecedents: Social Norms (Social Influence, Status). Mediators: Personal Norms (Privacy concern, Trust, Societal Impact), Control Beliefs (Self-efficacy, Personal innovativeness, Anxiety, Safety, Cost), Utilitarian Attitudes (Ease of use, Adaptability), Hedonic Attitudes (Enjoyment, Attractiveness, Animacy, Social presence, Sociability, Companion). Outcomes: Use Intention	Fully supported: Social Norms –>Personal Norms; Social Norms –>Control Beliefs Partially supported: Personal Norms, Social Norms, Hedonic Attitudes, Control Beliefs –>Use Intention; Control Beliefs –>Utilitarian Attitudes; Personal Norms, Social Norms, Control Beliefs –>Hedonic Attitudes

Ghazali, A.S, Jaap Ham, J., Barakova, E., Markopoulos, P. (2020)	SociBot	Antecedents: Enjoy. Mediators: Liking, Compliance, Beliefs, Attitude, Reactance, Usefulness, Ease. Outcomes: Intention to use	Liking, Attitude, Enjoy –>Intentions; Beliefs, Usefulness, Ease, Enjoy –>Attitude; Ease, Enjoy –>Liking; Beliefs –>Compliance; Liking –>Beliefs; Liking, Beliefs –>Reactance; Beliefs, Ease –>Usefulness; Enjoy –>Ease
Turja T, Aaltonen I, Taipale S, Oksanen A. (2020)	Robots: Double, NAO, Paro Seal, RIBA bear. Use of images.	Antecedents: Perceived Technology Unemployment, Attitude, Ease of use, Enjoyment, Trust. Mediators: Personal Values, Social influence, Usefulness. Outcomes: Intention to Use	Attitude, Enjoyment, Perceived Usefulness, Social Influence –>Intention to Use; Personal Values –>Perceived Usefulness; Personal Values –>Social Influence; Perceived Technology Unemployment –>Personal Values
Belanche, D., Casaló, L. V., Schepers, J., & Flavián, C. (2021).	Frontline robot named Casey performing waiter tasks. Use of images.	Antecedents: Humanness (Human-Likeness, Competence, Warmth). Mediators: Value (Functional, Social, Monetary, Emotional) Moderators: Need for social interaction. Outcomes: Loyalty	Emotional Value, Monetary Value, Functional Value –>Loyalty Intentions; Human-Likeness, Perceived Competence –>Functional Value; Human-Likeness –>Social Value; Human-Likeness, Perceived Competence –>Monetary Value; Human-Likeness, Perceived Competence, Perceived Warmth –>Emotional Value. Moderating effects by Need for social interaction: Human-Likeness –>Functional Value; Perceived Warmth –>Social Value; Human-Likeness, Perceived Warmth –>Emotional Value
Forgas-Coll, S., Huertas-Garcia, R., Andriella, A., & Alenyà, G. (2022a).	TIAGo Semi-Humanoid Robot	Antecedents: Adaptiveness, Sociability. Mediators: Perceived Usefulness, Ease of Use, Enjoyment, Social Influence. Moderators: Gender and personality stereotypes. Outcomes: Intention to use	Perceived Usefulness, Perceived Enjoyment, Social influence –>Intention to Use; Perceived Ease of Use, Perceived Adaptiveness –>Perceived Usefulness; Perceived Adaptiveness, Perceived Sociability –>Perceived Enjoyment. Moderating effects by gender and personality stereotypes: Female/Cooperative (P. usefulness, Social influence –>Intention to use; P. adaptiveness –>P. usefulness; P. adaptiveness, P.sociability –>P. Enjoyment), Male/Cooperative (P. usefulness, P.ease of use, P. enjoyment –>Intention to use; P. adaptiveness –>P. usefulness; P. adaptiveness, P.sociability –>P. Enjoyment), Female/Competitive (P. usefulness, Social influence –>Intention to use; P. adaptiveness –>P. usefulness; P. adaptiveness, P.sociability –>P. Enjoyment), Male/Competitive (P. usefulness, P.ease of use, Social influence; P. adaptiveness –>P. usefulness; P. adaptiveness –>P. Enjoyment)

Hyun, Y., Hlee, S., Park, J. & Chang, Y. (2022)	Robot waiter (no name specified)	Antecedents: Socio-Functional Elements: Perceived Hospitability, Perceived Coolness, Perceived Robot Safety, Robot Performance Competence. Mediators: Experiential Outcomes, Instrumental Outcomes, Viability of Human-Robot Team Service. Moderators: Personal Innovativeness. Outcomes: Intention to use Service Robots	Viability of Human, Experiential outcomes, Instrumental Outcomes –>Intention to use; Experiential Outcomes, Instrumental Outcomes –>Viability of Human-Robot Team Service; Perceived Hospitality, Perceived Coolness, Robot Performance Competence –>Experiential Outcomes; Perceived Hospitability, Perceived Robot Safety, Robot Performance Competence –>Instrumental Outcomes Moderating effects by Personal Innovativeness: Perceived Robot Safety, Robot Performance Competence –>Instrumental Outcomes
Subero-Navarro, A., Pelegrín-Borondo, J., Reinares-Lara, E., & Olarte-Pascual, C. (2022).	Not specified.	Antecedents: Cognitive dimension (Effort expectancy, Performance expectancy), Affective dimension (Pleasure, Arousal), Normative dimension (Social Influecne), Visceral component (Technophobia). Outcomes: Intention to use	Effort expectancy, Pleasure, Social Influence, Technophobia –>Intention to use