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FRONTLINE EMPLOYEES' ATTITUDE TOWARD EMBODIED SOCIAL ROBOTS IN CUSTOMER SERVICE:

AN INTEGRATIVE FRAMEWORK AND EMPIRICAL TEST

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Frontline Employees' Attitude toward Embodied Social Robots in Customer Service: An Integrative Framework and Empirical Test

Embodied social robots—robots providing services for and in cocreation with consumers—are expected to profoundly change the way services are delivered. Yet, their integration in customer service poses a challenge: their adoption by frontline employees (FLEs). Accordingly, this study aims to examine FLEs' attitude toward embodied social robots and to uncover its antecedents. This work presents an integrative framework which builds upon the technology acceptance model and examines the influence of potential factors on FLEs' attitude toward embodied social robots. An online survey among 165 FLEs is used to test the integrative framework. Despite the growing knowledge regarding customers' perceptions of (embodied social) robots, the perspective of FLEs is under-investigated while crucial to foster FLEs' acceptance of such robots. This research concludes with several strategies service providers can implement to possibly enhance FLEs' attitude toward embodied social robots, and thus, to support their adoption by FLEs.

Keywords: social robots, frontline employees, human-robot interaction, technology acceptance, customer service

Paper type: Research paper

1. Introduction

The combination of robotics and rapidly improving technologies, such as artificial intelligence (AI), has the potential to radically change service industries (Wirtz *et al*., 2018). Robotics and AI offer service providers a wide range of benefits, including cost reductions, productivity gains, increased revenues, and improved customer retention (Lu *et al*., 2020; Schepers and Streukens, 2022). These technologies affect consumer experience and the process of service delivery (Lu *et al*., 2019) while providing organizations with exciting opportunities for innovation (Wirtz *et al*., 2018). Over the last decade, service robots—a technology at the interface between robotics and AI—took off in service sectors, such as retail and hospitality (Wirtz *et al*., 2018). According to the International Federation of Robotics (2021), in 2020, the market size of service robots represented US$ 6.7 bn and has increased by 12% (IFR, 2021). Thanks to developments in 5G telecom services, wireless connectivity, and advanced AI chips, service robots are becoming increasingly appealing to businesses.

There is a wide range of service robots (Schepers and Streukens, 2022; Wirtz *et al.*, 2018). In this study, we focus on physical robots that can perform social tasks (i.e., social robots). More specifically, we focus on 'embodied social robots'—that is autonomous robots that can interact socially with consumers and employees while providing services for and in cocreation with consumers and employees (Blaurock *et al.*, 2022a). In frontline service settings, these are usually humanoid robots able to perform increasingly emotional-social tasks (Meyer *et al*., 2020)—as they are developed for interaction with humans (i.e., customers and frontline employees). For service providers, introducing embodied social robots in the frontline represents an opportunity for innovation as much as a challenge: that of user acceptance (Meyer *et al*., 2020).

To date, while the service literature heavily focuses on customer acceptance of service robots (De Keyser and Kunz, 2022), research rarely addresses the issue from the perspective of frontline employees (FLEs) (Meyer *et al*., 2020)—resulting in a lack of crucial insight regarding their perceptions of robots at the frontline (De Keyser and Kunz, 2022; Subramony *et al*., 2018). FLEs' acceptance of embodied social robots, however, is key to implement these in the frontline (Meyer *et al*., 2020). Organizational changes—especially those related to technology—can lead to uncertainty and resistance from employees (Shah *et al*., 2017). FLEs can perceive embodied social robots as threatening in their service jobs owing to concerns such as loss of autonomy (Lu *et al*., 2020). Addressing the perspective of FLEs and understanding their acceptance of embodied social robots, therefore, represent a real research opportunity (Wirtz *et al*., 2018)—as illustrated by De Keyser and Kunz (2022, p. 177): "several of the experts stress the need to consider the employee side to understand how human employees react to and may develop strong working relations with service robots". Thus, a better understanding of the FLE perspective would help avoid failures, both technical (e.g., software and hardware failures) or interactive (e.g., human errors, communicating failures) (Honig and Oron-Gilad, 2018), and identify strategies that could motivate FLEs to work and collaborate with robots at the frontline.

FLEs' positive attitude toward embodied social robots is key to their successful engagement with them—as, according to the theory of reasoned action, a positive attitude toward a new behavior (e.g., adopting a new service technology such as an embodied social robot) is a key antecedent of the intention to adopt the behavior, which, in turn, is a key antecedent of actual behavior (Fishbein and Ajzen, 1975). Thus, behaviors and behavioral intentions are determined by positive attitudes toward the new behavior.

Therefore, this study focuses on FLEs' attitude toward embodied social robots and its antecedents. Specifically, the present study aims to (1) examine FLEs' attitude toward embodied social robots, (2) uncover the factors influencing their attitude toward this technology, and (3) identify actions that service providers can undertake to enhance FLEs' acceptance of robots at the frontline. To achieve this goal, this paper proposes an integrative framework that explains FLEs' attitude toward embodied social robots drawing on prior research and technology acceptance models, including the technology acceptance model (Davis *et al*., 1989), the social frontline robot acceptance model (Stock and Merkle, 2017), and the service robot acceptance model (Wirtz *et al*., 2018).

The present paper contributes, both theoretically and managerially, to the literature on robots in customer service, with a focus on the FLE point of view. Specifically, the paper expands emerging research on employees' perceptions of technological advances, and responds to recent calls to examine FLEs' perceptions of (embodied social) robots and understand their willingness to work with such robots (De Keyser and Kunz, 2022; Lu *et al*., 2020; Wirtz *et al*., 2018). A few emerging studies have adopted a conceptual (e.g., Xiao and Kumar, 2021) or qualitative design (e.g., Paluch *et al.,* 2022) to uncover potential drivers of FLEs' acceptance of service robots. The present investigation builds on their findings and follows Meyer *et al*.'s (2020) recommendation to perform a quantitative study on the present topic of interest. Finally, the integrative theoretical framework—and its empirical validation—can provide managers with useful insights to enhance FLEs' adoption of embodied social robots.

From a managerial perspective, the present paper contributes to the future of service organizations in assisting technology providers and service providers when making strategic decisions regarding customer service encounter design and management. In fact, the present work deepens managers' understanding of FLEs' perceptions with the view of overcoming potential resistance in their teams. The study concludes with strategies that managers can use to prevent negative attitudes among FLEs while increasing FLEs' acceptance of embodied social robots.

2. Literature review

2.1 Embodied social robots in customer service

Wirtz *et al*. (2018) underline three design attributes of robots in service contexts: representation, anthropomorphism, and task orientation. They can be physically or virtually represented (e.g., Pepper vs. Alexa), have a humanoid or non-humanoid design (e.g., Sophia vs. Roomba cleaning robot), and perform cognitive-analytical or emotional-social tasks (e.g., an image analysis software assistant for medical diagnosis vs. reception robots). The present study focuses on embodied social–that is, physically represented humanoid robots which can perform emotional-social tasks. They are autonomous robots that can interact socially with consumers and employees while providing services for and in cocreation with consumers and employees (Blaurock *et al.*, 2022a).

Due to their innovative potential in retail and customer service (Grewal *et al.*, 2017) and due to their ability to provide tangible services to customers (Wirtz *et al.*, 2018), embodied social robots are increasingly used at the frontline, in a variety of service industries, such as airlines, hotels, restaurants, and retail, to perform customer services (Lu *et al.*, 2019; Xiao and Kumar, 2021). In particular, they can provide personalized service to customers at negligible marginal cost (Wirtz *et al.*, 2018) while keeping customers safe from being infected from viruses (Schepers and Streukens, 2022).

2.2 FLEs and social robots in services

Most research on the acceptance of (embodied social) robots in the service context focuses on the customer's perspective. As evidenced in Tab. 1, a number of recent studies have investigated users' acceptance of robots in services. In particular, this growing academic interest mainly focuses on customers' interaction with (e.g., Lu *et al*., 2020), perception of (e.g., Wirtz *et al.*, 2018), and response to (e.g., Oderkerken-Schröder *et al.*, 2022) robots, both in domestic (e.g., Hameed *et al*., 2016) as well as service contexts (e.g., Stock and Merkle, 2017).

In a recent article, De Keyser and Kunz (2021) systematically examined 173 individual studies on robots in services. While 89.60% of those studies focus on customers, only 5.78% (i.e., 10 individual studies) focus on employees (e.g., Henkel *et al.*, 2020; Paluch *et al.*, 2022) Thus, the literature digging into employee attitude toward robots—and more particular into FLEs' attitude toward embodied social robots—is still in a nascent stage. While studies have shown the managerial configurations and role structures according to which technology, such as embodied social robots, and FLEs can co-exist (Bowen, 2016; Larivière *et al*., 2017; Keating *et al*., 2018), or even sought to predict the future of human employment post-technology-adoption (Broughman and Haar, 2018; Huang and Rust, 2018; Davenport *et al*., 2020), further knowledge on how FLEs respond to (embodied) social robots remains necessary. Indeed, it is crucial to understand FLEs' attitude toward robots, as FLEs are an organization's most important asset and a source of competitive advantage (Wirtz *et al*., 2018). Technological developments transform service interactions and the role of humans who are empowered through digital devices (Keating *et al*., 2018). Consequently, FLEs need to adjust to technologies, upgrade and acquire new sets of skills (Huang and Rust, 2018; Lu *et al.*, 2020), and essentially, be able to deal with technology as a new 'partner' (Larivière *et al*., 2017) to drive service quality (Xiao and Kumar, 2021).

Understanding why FLEs respond in specific ways to technology is particularly relevant, as recent studies indicate that they are affected by smart technologies and connected objects (De Keyser *et al*., 2019). According to Larivière *et al*. (2017), if employees are not ready to meet the new job requirements, their performance can decrease. The morale and productivity of FLEs may also decline due to a lack of confidence and comfort using technology-based service options (Parasuraman and Colby, 2015). The extent to which employees feel that their job could be replaced by technology is negatively related to organizational commitment and career satisfaction, and positively related to turnover intentions, cynicism, and depression (Brougham and Haar, 2018). As a result, service providers must reduce any potential adverse effects on employees (Parasuraman and Colby, 2015) as well as understand how to increase FLEs' motivations to robot usage.

Study	**Research objectives**	**Method & sample**	**Context**	**User focus**
Blaurock *et al.* (2022a)	Interdisciplinary review of research on human-robot service interactions	Review of 199 articles	Across service contexts	Customers
Blaurock *et al.* (2022b)	Interdisciplinary review of research on human-robot service interactions from a role theory perspective	Review of 139 articles	Across service contexts	Customers
De Keyser and Kunz (2022)	Comprehensive review of service robot research published in the area of service research	Review of 88 articles Interviews: 79 researchers	Across service contexts	FLEs and customers
Oderkerken-Schröder *et al.* (2022)	Customers' repatronage intentions after interactions with both service robots and FLEs	Field study: 108 customers Experimental study: 361 participants	Retail	Customers
Paluch *et al.* (2022)	FLE's willingness to work with service robots	Qualitative: 36 FLEs	Across service contexts	FLEs
Xiao and Kumar (2021)	FLEs' and customers' acceptance of service robots as well as their effects	Conceptual	Across service contexts	FLEs and customers
Choi *et al*. (2020)	Influence of human-robot interactions on service quality	Focus groups: 16 hotel managers Experimental study: 339 participants	Tourism and hospitality	Customers
Henkel *et al*. (2020)	Influence of an AI-based recognition software on FLE goal attainment and wellbeing	Field study: 2,459 service interactions	Financial services	FLEs
Lu *et al.* (2020)	Review of research on the impact of service robots on customers and employees	20 articles	Across service contexts	FLEs and customers
Meyer *et al.* (2020)	Acceptance of service robots by FLEs	Qualitative: 24 FLEs	Retail	FLEs
Lu *et al.* (2019)	Customers' long-term willingness to integrate AI and service robots into regular service transactions	Scale development: 1348 participants (students and workers)	Tourism and hospitality	Customers
Wirtz *et al.* (2018)	Potential role service robots will play in the future	Conceptual	Across service contexts	FLEs and customers
Stock and Merkle (2017)	Acceptance of frontline service robots during service encounters	Interviews: 63 participants Experimental study: 82 students	Across service contexts	Customers
van Doorn *et al.* (2017)	Impact of automated social presence on service and customer outcomes	Conceptual	Across service contexts	Customers
Hameed *et al.* (2016)	User acceptance of social robots	Experimental study: 97 participants	Domestic	Customers
de Graaf and Ben Allouch (2013)	User acceptance of social robots	Experimental study: 60 students	Domestic	Customers
Park and del Pobil (2013)	User acceptance of service robots	Web-based survey: 904 users	Domestic	Customers

Tab. 1. Overview of articles examining user acceptance of service robots

Research on service robots taking the perspective of FLEs currently focuses on comparing service robots' capabilities with those of FLEs' (e.g. De Keyser and Kunz, 2022; Wirtz *et al.*, 2018). Additionally, the impact of service robots on FLEs has also been investigated in the literature, suggesting enhanced productivity, opportunities for collaboration or wellbeing, but also job insecurity or loss of autonomy (Henkel *et al*., 2020; Lu *et al*., 2020). More recently, a few studies have adopted qualitative designs to explore FLEs' acceptance of service robots. Notably, five aspects of FLEs' acceptance of and resistance to service robots; i.e., loss of status, tension, required commitment, role incongruency, and advocation, were highlighted by Meyer and colleagues (2020). Further, robot attributes (i.e., autonomy, social presence, humanoid), job attributes (i.e., job types, roles, necessary skills) and individual characteristics (i.e., technology readiness, robot bias) seem to play an important role in shaping FLEs' willingness to collaborate with service robots (Paluch *et al*., 2022). Recent conceptual insights also bring some clue regarding FLEs' acceptance of service robots, highlighting the potential importance of their perceived usefulness, ease-of-use, as well as their fit with the job and profession targeted (Xiao and Kumar, 2021).

To conclude, the literature not only shows the increasing relevance of robots as partners in delivering services, but also, and most importantly, the comparative lack of research on FLEs versus customers with regard to social robots (De Keyser and Kunz, 2022; Larivière *et al*., 2017; Brougham and Haar, 2018; Meyer *et al*., 2020). More research, including quantitative studies, is needed on FLEs' perceptions of working and collaborating with social robots (De Keyser and Kunz, 2022; Lu *et al*., 2019; Meyer *et al*., 2020)—with the ultimate goal to enable scholars and practitioners to understand the changing service industry, and to adequately prepare employees, employers, governments, and policy makers for the potential changes (Brougham and Haar, 2018).

3. Hypotheses development

The present research aims to investigate FLEs' perceptions of embodied social robots and to understand their acceptance of this emerging technology. According to the technology acceptance model (TAM), stemming from the theory of reasoned action (TRA), users' adoption of new technologies in an organizational context is influenced by their attitude—whether generally favorable or not—toward them (Davis *et al*., 1989). The TAM initially aims to explain user acceptance and rejection of computer-based technology and states that a positive attitude toward technology has a significant influence on adoption behaviors (Davis *et al*., 1989). A common attempt to investigate users' acceptance of robots, therefore, focuses on their attitude toward them (e.g., Park and del Pobil, 2013; Savela *et al*., 2018; You and Robert, 2018). For this reason, the proposed integrative framework addresses FLEs' attitude toward embodied social robots and the potential factors likely to influence it (see Fig. 1).

3.1 FLEs' perceived ease of use and usefulness of embodied social robots

The TAM postulates that perceived usefulness and perceived ease of use are key determinants of user acceptance behavior (Davis *et al*., 1989). Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance", while perceived ease of use refers to "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). These two constructs are distinct yet related. Indeed, Davis (1989) argues that usefulness exerts a positive influence on users' attitude toward using a system, whereas "ease of use operates through usefulness" (p. 332). According to the author, the easier a system is to use, the more effort can be devoted to other activities, which contributes to improved job performance. Hence, ease of use would have a direct effect on usefulness. These key relationships underlying the TAM have been supported by numerous studies, including Park and del Pobil's study on service robots (2013). Also, in the social frontline robot acceptance model (SFRAM), the functional components of robot acceptance include two sub-dimensions: perceived usefulness and perceived ease of use (Stock and Merkle, 2017). Along those lines, several conceptual and qualitative studies in the service context advance the potential importance of perceived usefulness and ease-of-use in influencing users' (including FLEs') acceptance of service robots (Lu *et al.*, 2019; Meyer *et al.*, 2020; Wirtz *et al.*, 2018; Xiao and Kumar, 2021). Thus, it is hypothesized that FLEs' perceived ease of use positively impacts FLEs' perceived usefulness, which in turn positively affects FLEs' attitude toward embodied social robots.

H1. FLEs' perceived ease of use of embodied social robots positively influences FLEs' perceived usefulness of those robots.

H2. FLEs' perceived usefulness of embodied social robots positively influences FLEs' attitude toward those robots.

3.2 FLEs' perceived sociability of embodied social robots

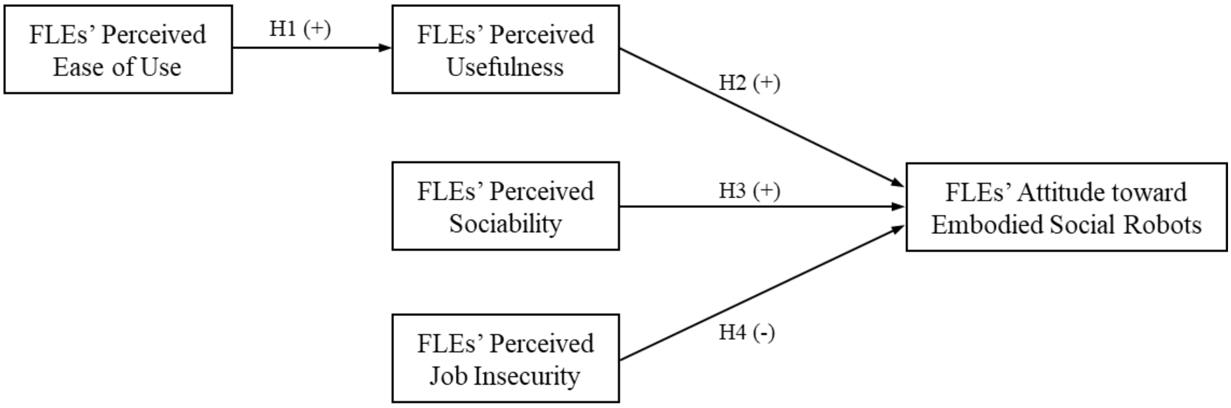
Designed for social interaction, embodied social robots require social skills (de Graaf and Ben Allouch, 2013). According to Stock and Merkle (2017), the relational components affecting customers' adoption of frontline service robots include the ability to understand their needs, especially in order to display the appropriate emotions accordingly (Wirtz *et al.*, 2018). From the perspective of FLEs, this social-emotional sensitivity of robots can be particularly important to be perceived as pleasant interaction partners and drive adoption (Meyer *et al.*, 2020) as well as to increase FLEs' willingness to collaborate with robots (Paluch *et al.*, 2022). All in all, robots' social capabilities (i.e., social interactive skills, social intelligence, emotion expression, and dialogue system) are expected to influence FLEs' acceptance (Hameed *et al.*, 2016). These social skills are grouped under the perceived sociability construct, which is defined as "the perceived ability of the system to perform sociable behavior" (Heerink *et al.*, 2009, p. 529). From what precedes, it can be expected that the perceived sociability of embodied social robots can strengthen FLEs' positive attitude toward them. Hence, the third hypothesis is proposed.

H3. FLEs' perceived sociability of embodied social robots positively influences FLEs' attitude toward those robots.

3.3 FLEs' perceived job insecurity

AI and robotic advances could be perceived as a threat to human employment (Huang and Rust, 2018), especially in the service sector (Brougham and Haar, 2018). Indeed, robots' capabilities can make FLEs fear for their job (Lu *et al*., 2020; Meyer *et al*., 2020), depending on the job type and demands (Paluch *et al*., 2022). Robotization of service offerings can therefore be stressful for FLEs due to their concern about job insecurity (Subramony *et al*., 2018), which is defined as "the perception of a potential threat to the continuity of the current job" (Heaney *et al*., 1994, p. 1431). Employees' perception of job insecurity related to technology-driven changes appears as an expectation of job cuts in the near future but also of job inexistence in the longer term (Nam, 2019). These concerns can represent a major barrier to service robot acceptance (Meyer *et al*., 2020). Employees' fear of losing their own jobs or their co-workers can lead to negative attitudes toward robots and a lower willingness to work with them (You and Robert, 2018). This fear is likely to be stronger toward embodied social robots considering they tend to share more and more similarities with FLEs such as increasing social skills–which leads to the fourth hypothesis (see Fig. 1 for an overview of the four hypotheses).

H4. FLEs' perceived job insecurity negatively influences FLEs' attitude toward embodied social robots.



Note: FLEs = frontline employees

Fig.1. Antecedents of FLEs' attitude toward embodied social robots

4. Research design

4.1 Method

To test the framework in Fig. 1, an online survey was developed. After being introduced to the study, participants (i.e., FLEs) were shown a short video featuring a humanoid social robot interacting with a consumer in a retail store. Subtitles were embedded into the video to communicate about the robot's capabilities. Observing that people with no experience of robots rely on social representations of their attributes and qualities, Savela *et al*. (2018) recommended using some type of illustration as a way to control the variance of imagination when measuring attitude toward robots.

Besides the video, an online questionnaire was designed (in English and French), consisting of structured questions aiming to measure the core constructs of the integrative framework. Participants were asked about the industry they worked in, the size of their company, their age, gender, position, and whether they were responsible for collaborators.

Before sharing the survey, two sets of pilot-tests were conducted online to eliminate potential problems, detect any cultural biases, make wording and layout clear as well as determine the time needed to fill it out. Following Malhotra *et al*.'s (2017) recommendations, the French version was pilot-tested on monolingual subjects in their native language, while the French and English versions were proposed to bilingual subjects. Eight FLEs participated in the pilot-tests, including five monolingual subjects and three bilingual subjects. They were asked to fill out the questionnaires and give comments on the content, wording, sequence, layout, and instructions. Minor changes were made on the basis of the participants' feedback.

4.2 Measures

The different constructs investigated in this study were measured using items from several validated scales that have been adapted to the context of the present research. A detailed list of all items used can be found in the Appendix. Attitude toward service robots was measured using a three-item scale adapted from Davis *et al*. (1989). Perceived usefulness and perceived ease of use were measured using three-item scales adapted from Davis (1989). Perceived sociability was captured using a three-item scale adapted from Heerink *et al*. (2009). Finally, perceived job insecurity was measured using a three-item scale adapted from De Witte (2000) and Hellgren *et al*. (1999). All items were measured on seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Finally, demographic characteristics—such as age, job tenure, gender, industry, position, company size, and responsibility—were asked (see Tab. 2 for an overview).

4.3 Participants

The survey used for this study was shared online to reach a broad range of FLEs working in various service industries. First, the subjects counting among the authors' acquaintances were approached through social media. After completing the questionnaire, they were asked to share it with other individuals from the population of interest. Additionally, the survey link was shared on Facebook groups of employees from different major retailers in Belgium. A total of 165 filled-out surveys, 68% of which by female participants, were collected (N = 165). The participants' ages ranged from 18 to 67 years (mean = 35 years, standard deviation = 14 years)—see Tab. 2.

		n	%
Gender	Male	53	32%
	Female	112	68%
Age	18-24	55	33%
	25-34	49	30%
	35-44	17	10%
	45-54	20	12%
	55-67	24	15%
Industry	Food	55	33%
	Furniture	14	9%
	Cosmetics	10	6%
	Clothing	36	22%
	Hospitality	14	9%
	Pharmacy	3	2%
	Sport and leisure	8	5%
	Telecommunication	8	5%
	Other	17	9%
Position	Worker	7	4%
	Employee	139	84%
	Manager	12	7%
	Officer	6	4%
	Other	1	1%
Company size	Small	66	40%
	Large	99	60%
Job tenure	1-10	121	73%
	11-20	18	11%
	21-30	12	7%
	31-42	14	9%
Responsibility	No	122	74%
	Yes	43	26%

Note: N = 165

Tab. 2. Participants' demographics

5. Results

5.1 Validity and reliability checks

Before evaluating the structural model, the validity and reliability of the data were examined. Concerning reliability, the analysis revealed that all constructs exhibit satisfactory internal consistency as Cronbach's alpha range from 0.90 to 0.96 (see Tab. 3). The convergent validity of the data was then tested. Accordingly, the (1) loadings of individual items, the (2) composite reliability (CR) of each reflective construct, together with the (3) average variance extracted (AVE) were tested. According to the criteria defined by Fornell and Larcker (1981), the loadings of the individual items must be at least 0.70 for the data to be considered valid. This criterion was fulfilled as all loadings are at least 0.89. Concerning the composite reliability of each construct, the recommended threshold is 0.8 (Fornell and Larcker, 1981)—which was met as all constructs had a CR of at least 0.94. The AVEs must be at least 0.5; this criterion was also fulfilled as AVEs were at least 0.84 (see Tab. 3 for an overview of the CRs and AVEs). From this, it is concluded that the data had sufficient levels of convergent validity among the reflective constructs. Next, the discriminant validity of the data was examined by comparing the correlation values presented in Tab. 3 with the square roots of the AVEs presented diagonally. The table shows that the square roots of the AVEs are consistently higher than the correlation values. These findings give evidence of discriminant validity.

Variable	α	CR	AVE	1	2	3	4	5
1. Attitude toward service robots	0.96	0.97	0.92	***0.96***				
2. Perceived usefulness	0.93	0.96	0.88	0.85	***0.92***			
3. Perceived ease of use	0.91	0.94	0.84	0.76	0.75	***0.92***		
4. Perceived sociability	0.90	0.94	0.84	0.76	0.69	0.69	***0.92***	
5. Job insecurity	0.95	0.97	0.91	-0.56	-0.43	-0.48	-0.47	***0.95***

Notes: All correlations are significant at $p < 0.001$; the square root of the AVE is on the diagonal; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted

Tab. 3. Descriptive statistics and correlations

5.2 Common method variance

As a single informant (i.e., FLEs) was used to capture all variables, a range of procedures were used in an attempt to minimize the potential for common method variance (Campbell and Fiske, 1959). First, the items were formulated as clearly, concisely, and specifically as possible. Second, computer-administered questionnaires were used, which should reduce social desirability biases (Podsakoff *et al.*, 2003). The questionnaire's introduction specified that this was anonymous. Third, the design of the web-based survey instrument made it impossible for respondents to retrieve their answers from earlier questions. Therefore, it was more difficult for them to maintain artificial consistency between answers or search for patterns in the questions, which helped control for both the consistency motive and social desirability biases (Podsakoff *et al.*, 2003). Fourth, Harman's one-factor test was used to test for common method variance (Podsakoff and Organ, 1986). A principal component factor analysis of the dependent and independent variables yielded two factors with eigenvalues higher than 1.0, while the first factor explained less than 63% of the total variance. As these statistics suggest the absence of one major factor (Podsakoff and Organ,1986), common method variance does not seem to be present in the data.

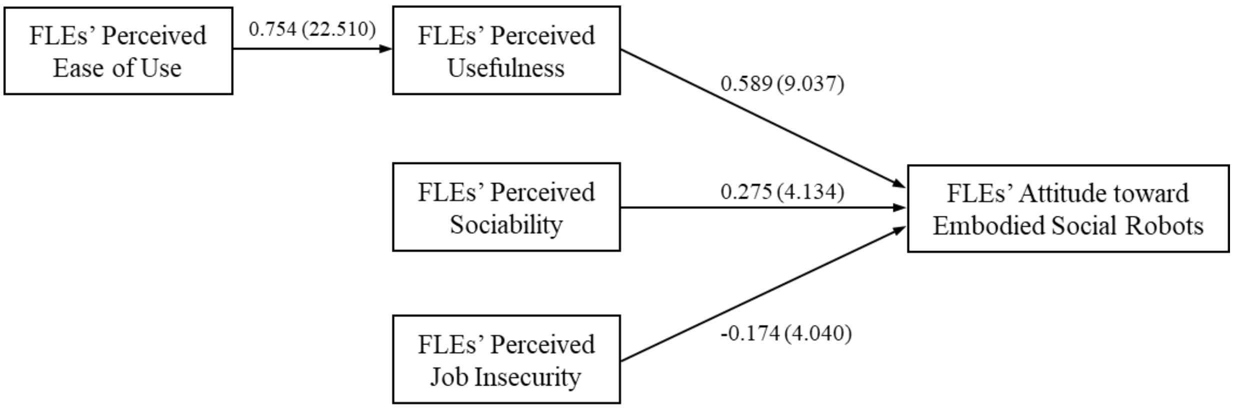
5.3 Model fit testing

After ensuring the validity and reliability of the data, the proposed research model was tested (see Fig. 2). The SmartPLS implementation of partial least squares (PLS) structural equation modeling was used to estimate the theoretical model (for an overview of its use, see Ringle *et al.*, 2012). PLS-SEM is recommended in different situations such as "when the research objective is to better understand increasing complexity by exploring theoretical extensions of established theories (exploratory research for theory development)" (Hair *et al.*, 2019, p. 5).

The explained variances (i.e., R^2 values) for perceived usefulness and FLEs' attitude toward service robots are 0.57 and 0.81, respectively—which indicates that the proposed conceptual model has adequate explanatory significance. Further, two model fitting parameters were used: the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). SRMR values less than 0.08 are considered a good fit while NFI values above 0.90 usually represent acceptable fit (Hair *et al.*, 2017). In the present study, the SRMR value is 0.055 (< 0.08) and the NFI is 0.88 (a value that is very close to 0.90)—indicating the data fits the model well.

5.4 Hypothesis testing

A bootstrapping procedure (500 subsamples; 165 cases) was applied to assess the significance of the path coefficients (Henseler *et al.*, 2009). The path estimates (i.e., β) and relative t-values of the structural model appear in Fig. 2 as the path coefficients were used to test the proposed hypotheses. The first hypothesis was supported as perceived ease of use positively influences perceived usefulness (standardized path coefficient = 0.754; t-value = 22.510). In support of H2, a significant, positive relationship was found between perceived usefulness and attitude toward service robots (standardized path coefficient = 0.589; t-value = 9.037). Support was also found for H3; there was a significant, positive relationship between perceived sociability and attitude toward service robots (standardized path coefficient = 0.275; t-value = 4.134). Finally, H4 was also supported as perceived job insecurity negatively influences attitude toward service robots (standardized path coefficient = -0.174; t-value = 4.040).



Note: Standardized path coefficients (i.e., β) and t-values (between brackets) are reported. All p values of the structural model are significant at: $p < 0.001$

Fig. 2. Structural model results

Further, the recommendations of Baron and Kenny (1986) were followed to test if perceived usefulness mediates the relationship between perceived ease of use and attitude toward service robots. A non-parametric bootstrapping procedure (Preacher and Hayes, 2008) revealed that perceived usefulness fully mediates the relationship between perceived ease of use and attitude.

6. Conclusion

The present study examines the perceptions of FLEs regarding the infusion of embodied social robots in customer service, with the view of uncovering the factors influencing their attitude toward this promising technology. Drawing on prior research, an integrative framework is proposed, empirically tested and validated. The results of the structural equation modeling confirm that perceived usefulness and perceived sociability positively influence FLEs' attitude toward embodied social robots, whereas perceived job insecurity affects it negatively. The findings also reveal that perceived usefulness is positively influenced by perceived ease of use, and mediates the relationship between perceived ease of use and attitude toward service robots.

These insights into FLEs' perceptions of embodied social robots have interesting theoretical as well as managerial implications.

6.1 Theoretical implications

This study contributes to the emerging literature on technological changes, focusing on the introduction of embodied social robots in customer service. First, an important theoretical contribution lies in the investigation of an emerging perspective for service research, that of FLEs. In fact, this study answers a call for further research on examining employee perceptions about service robots. Indeed, De Keyser and Kunz (2022, p. 177) recently state: "research is needed to understand how internal firm processes should be adapted when integrating service robots, how service robots impact the organizational culture and what internal and external enablers vs barriers are driving/hindering their successful implementation". Therefore, by examining FLEs' attitudes toward embodied social robots and what might influence it, we aim to contribute to this nascent field of research. As highlighted by Wirtz et al. (2018), various key stakeholders must be examined when studying robots: customers, service firms, but also (frontline) employees. Those three stakeholders are best represented in a triangle relationship with robots at the heart of the triangle while each key stakeholder represents one of the three corners of the triangle.

Second, the present work also contributes to human-robot interaction research by examining simultaneously a combination of variables that could lead to the acceptance of embodied social robot by FLEs. In particular, we show in a structural comprehensive model that FLEs' perceived usefulness and sociability of robots positively influence FLEs' attitude toward robots—while FLEs' perceived job insecurity negatively influence FLEs' attitude toward robots. Those results are consistent with Meyer *et al.*'s study (2020) who found that perceived job insecurity is a barrier to FLEs' acceptance of robots, which implies that the more

FLEs perceive robots as a potential threat to the continuity of their job, the less favorable they will be toward working with them. These findings accord with previous research on employee perceptions of technology. For instance, You and Robert (2018) mention that employees' negative attitude toward robots can be engendered by the fear that robots will eventually take their jobs. Nam (2019) also highlights the close link between employees' perceptions of job insecurity and attitude toward the adoption of technologies.

Third, the findings show that perceived ease of use positively influences perceived usefulness, which in turn exerts a positive influence on attitude toward embodied social robots. In fact, the more FLEs perceive embodied social robots as easy to use and to interact with, the more they believe that their use will increase their work performance, and the more favorable they will be toward them. The study therefore confirms these key relationships and discloses the mediating role of perceived usefulness in the relationship between perceived ease of use and attitude. As well, the data support previous studies and models: namely SFRAM and sRAM, which consider perceived usefulness and perceived ease of use key drivers of service robot acceptance (Stock and Merkle, 2017; Wirtz *et al*., 2018), and the model of Meyer *et al*. (2020), which reveals that FLEs are more likely to adopt embodied social robots if practical advantages are perceived. Such practical advantages are likely to be particularly prevalent in situations of "augmentation" of the service employee, that is to say when technologies supplement the service employee's role and capabilities (Larivière *et al.*, 2017; Blaurock *et al.*, 2022b) as a clear functional benefit of better serving customers appear. The technology is also likely to be valuable in instances of "substitution", for more repetitive and mindless tasks, in which ease of use is of particular relevance, as the easier a mindless task is to perform, the more satisfactory (Larivière *et al.*, 2017).

Fourth, the findings show that perceived sociability positively affects attitude toward embodied social robots, thus acting as a driver of FLEs' acceptance of embodied social robots.

Indeed, it was suggested that the favorableness of FLEs to work with robots depends on the robots' abilities to perform sociable behavior, such as displaying appropriate emotions (Wirtz *et al*., 2018), understanding users, and providing logical answers (Hameed *et al*., 2016). In a qualitative study, Meyer *et al*. (2020) also suggest that the quality and pleasantness of interactions are important for FLEs in the adoption of service robots. We show in a quantitative study the importance of robots' sociability in enhancing FLEs' attitude toward robots—above and beyond other key antecedents of FLEs' attitude toward robots. Accordingly, scholars could further examine which (combination of) aspects of robots could enhance FLEs' perceived sociability of robots (tone of voice, type of smile and eye contact, type of rapport-building behaviors…).

6.2 Managerial implications

It appears from the data that FLEs' attitude toward service robots is positively influenced by the perceived usefulness and the perceived sociability of the technology while being negatively influenced by perceived job insecurity. Additionally, the perceived ease of use of service robots is found to positively impact their perceived usefulness. Such findings have three main managerial implications to overcome FLEs' negative attitude toward service robots and increase their overall acceptance in the workplace.

First, the perceived usefulness of embodied social robots, which is influenced by their perceived ease of use, is found to be a predictor of FLEs' positive attitude toward the technology. Consequently, managers should consider showcasing the user-friendliness of robots they wish to implement in their organizations by, for instance, providing training sessions in which their employees can interact and experiment with the robots beforehand; such opportunities might change their view of the effort needed to efficiently work with them. As well, clear information concerning the robots' various abilities and specific tasks would boost FLEs' confidence that these digital 'colleagues' will effectively help them better execute their job. On the manufacturer's side, ensuring that robots are well-designed, user-friendly, and user-centric for both FLEs and customers is a crucial requirement.

Second, positive attitudes were also found to be fostered thanks to the perceived social skills of robots. In this regard, robot providers should strive to create robots that are social creatures, competent in social situations, and able to communicate in a similar way to humans, especially by using voice as well as facial and emotional recognition sensors. It is up to service managers to choose the best suited robot to their context, considering that its relative social intelligence and skills may condition its successful implementation and acceptance by FLEs. The right amount of sociability needs to be carefully crafted, so as to generate positive attitudes without being threatening for FLEs. These skills could further be promoted through real-life demonstrations.

Third, the findings show that attitudes could be impacted negatively by the fact that FLEs regard embodied social robots as a threat to the continuity of their job. So, it is important for managers to be transparent regarding the changes coming ahead in their organizations and their exact motivations for implementing such technology. The specific roles of FLEs and embodied social robots should be precisely defined and delineated, and FLEs should be given space to undertake more customer-oriented work and be encouraged to collaborate with embodied social robots to take advantage of their mix of skills when delivering services. In short, embodied social robots should be perceived by FLEs as an augmenting rather than a substituting force, and should always complement staff with the view of delivering the best service experience to consumers. In particular, when FLEs consider robots to be at threat—which could be the case when they perceive robots to be not only useful but also sociable—FLEs' concerns for job insecurity can be high. Therefore, to lower FLEs' concerns for job insecurity, managers could exchange with their FLEs' on how robots can be reliable subordinates for simple cognitive and/or emotional tasks while enhancing FLES' job conditions by helping FLEs to focus on key and complex tasks requiring high cognitive and/or emotional skills—that cannot be achieved by robots. Further, it could be also suggested to designers that a subtle trade-off is necessary when designing robots: while robots should be (perceived as) useful and sociable, robots should stay distinct from FLEs' strengths and characteristics to avoid FLEs' fear for job insecurity due to perceived substitution of FLEs' by robots.

6.3 Limitations and further research

While this study provides insights into FLEs' perceptions of embodied social robots, it has some limitations. First, the sample size hinders generalizing the results. Also, quick and inexpensive a method as it is, judgmental sampling does not allow direct generalization to a particular population (Malhotra *et al.*, 2017). Further research could therefore replicate this study with a wider audience and use respondents that are more representative of the population, such as respondents recruited through probability sampling.

Second, participants were introduced to an embodied social robot through a video. The results may differ from a study where participants are directly exposed to such a robot in a real-life context (You and Robert, 2018; Savela *et al*., 2018). It could therefore be relevant to conduct such a study and compare the results with ours. Further, a real-life context could also extent the study to incorporate actual responses and engagement of FLEs toward the technology, beyond attitudes.

Third, a limited set of variables were identified as core determinants of FLEs' attitude toward embodied social robots. Further elaborations of the model could include and test additional variables such as, for instance, the anthropomorphism of robots (van Doorn *et al,* 2017). Studies also suggest that for consumers, robot usage also depends on consumers' preferences, role enactment (Blaurock *et al.*, 2022b) attribution of responsibility (Jörling *et al.*, 2019), or even type of situation (Pitardi *et al.*, 2022). FLEs' job (in)security in the age of social robots may thus require the investigation of different types of contexts and situations.

Fourth, cross-sectional designs also bring limitations. An experimental research design would help identifying with more accuracy the specific context and conditions under which FLEs' attitude toward embodied service robot vary, which may be linked to robot, or employee characteristics (Paluch *et al.*, 2022) and roles, as well as industry or service type.

Fifth, an experimental study could be done to best understand the relationships between the variables of our model. For instance, an experimental design could allow to determine if usefulness and sociability of robots could generate fear of job insecurity among FLEs. Indeed, job insecurity could occur if high levels of usefulness and sociability among robots are achieved—as a consequence of the increasing qualities of robots that used to be unique to human employees. Thus, such a 3*3 between-subjects factorial design (both usefulness and sociability would vary according to three levels: low, medium, high) could help to precisely determine the optimal levels of usefulness and sociability of robots to minimize FLEs' perceptions of job insecurity.

Finally, the emergence of embodied social robots raises a wide range of ethical concerns deserving researchers' special attention, such as the moral intelligence and rights of service robots, the specific ethical norms applicable to the implementation of service robots and the prevention of unethical behaviors of robots (Lu *et al.*, 2020). Ultimately, users' perceptions might change as robotics develops functional, emotional-social, and relational components. Therefore, FLEs' perceptions of embodied social robots should be studied over time.

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Appendix: Questionnaire items

Construct	Items
Attitude toward service robots (adapted from Davis *et al.*, 1989)	1. I believe it is a good idea to use service robots 2. I would enjoy working with service robots 3. I have a generally favorable attitude toward service robots
Perceived usefulness (adapted from Davis, 1989)	1. I think that service robots are useful 2. Service robots would enable me to accomplish tasks more quickly 3. Service robots would increase my productivity
Perceived ease of use (adapted from Davis, 1989)	1. It would be easy for me to interact with service robots 2. Learning to use service robots would be easy for me 3. I would find service robots easy to use
Perceived sociability (adapted from Heerink *et al.*, 2009)	1. I would consider service robots pleasant conversational partners 2. I would find service robots pleasant to interact with 3. I feel service robots would understand me
Perceived job insecurity (adapted from De Witte, 2000; Hellgren *et al.*, 1999)	1. I feel insecure about the future of my job due to service robots 2. I think I might lose my job in the future due to service robots 3. I believe that the organization will need my competence also in the future *

* Reversed item

Note: Considering the time constraints of the population of interest (FLEs), when the measure included more than three items, only three items were included to keep the survey as short as possible to maximize the response rate. Doing so allowed the authors to test the model while preventing respondents' fatigue due to a lengthy questionnaire with questions that may be perceived as similar.