Are Retail Customers Ready for Service Robot Assistants?

Irene Roozen[1] · Mariet Raedts[2] · Anna Yanycheva[1]

Abstract

The use of service robots is rapidly expanding in many industries, including the retail sector. In some Asian countries retail companies already deploy in-store humanoid robot assistants that interact with customers in a personalized and dynamic way. However, little is known about customers' perceptions of these robot-assisted interactions. Therefore, we compared customers' perceived service quality of a human-robot interaction with a human-human interaction in a retail store, using an experiment with hypothetical scenarios (N = 425). Participants' general attitudes towards robots, their age, gender, and educational level were included as moderators in the analyses (a mixed-design ANOVA model). Results showed that participants valued service quality higher in the human-human interaction scenario. Additionally, findings from the moderation analyses indicated that perceived service quality of the human- robot interaction and the human-human interaction did not statistically significantly differ for participants with relatively high positive attitudes towards robots. Participants with relatively low positive attitudes towards robots, however, held statistically significantly lower perceptions of service quality for the human-robot interaction. Neither age, gender nor educational level statistically significantly influenced participants' perceived service quality scores for both service encounters.

Keywords service robot · service quality · human-robot interaction · attitude towards robots · SERVPERF · NARS

1 Introduction

The presence of frontline service robots in store aisles of retail shops is no longer futuristic (Bogue, 2019; Grewal et al., 2020). Frontline service robots are defined as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 909). One of these service robot examples is the 'LoweBot'. It was launched in 2016, and was developed specifically for Lowe's, the American retail company for home improvements (Bogue, 2019). The LoweBot can greet customers and helps them find items in the store (Hullinger 2016). Another example of a frontline service robot is the humanoid robot Pepper (SoftBank Robotics, n.d.). It is widely used in retail shops for greeting customers, providing directions and serving customers' requests. Pepper is capable of natural interaction with customers and understands and speaks 15 languages (Bogue, 2019).

Frontline service robots in retail stores enhance work efficiency: they never get tired, and perform stock-tracking tasks faster than human employees (Robots.net, 2019). Given the considerable benefits of service robots, it is not surprising that sales of professional service robots have increased by 32% between 2018 and 2019 (International Federation of Robotics, 2020). Moreover, the International Federation of Robotics (IFR, 2020) forecasts that robots will be even more involved in professional tasks in the near future. Service robots are expected to change the way we shop at retail stores. In the near future all service robots will be connected into one big ecosystem and will be able to access information, not solely through their local input channels like sensors, cameras and microphones, but also through external sources such as the Internet and CRM-systems (Wirtz et al.,

✉ Irene Roozen
  irene.roozen@kuleuven.be

  Mariet Raedts
  mariet.raedts@uantwerpen.be

  Anna Yanycheva
  ann.yanycheva@gmail.com

1 Faculty of Economics and Business, Department of Marketing, KU Leuven, Leuven, Belgium

2 Faculty of Arts, Department of Linguistics, University of Antwerp, Antwerp, Belgium

2018). The combination with biometrics (facial and voice recognition) will enable retail service robots to provide customers with highly personalized services at low marginal costs based on customer purchase history and preferences.

Frontline service robots thus have many advantages at first glance, but empirical studies on the effectiveness of robotic customer assistance in a retail environment are nearly non-existent (Belanche et al., 2020). In order to address the effectiveness of human- robot service encounters, we compared customers' perceived service quality of a human-human interaction in a shoe shop setting with their perceptions of the service quality offered by a frontline service robot (human-robot interaction). Participants' general attitudes towards robots were added to the model as a moderator to test whether the effect of service encounter type (human- robot versus human-human) differed across people with relatively high positive or relatively low positive attitudes towards service robots. Finally, participants' age, gender and educational level were measured in order to examine their moderating effects as well. The findings of our study will help managers of retail stores to better understand (differences in) consumers' evaluations of interactions with frontline service robots, so that they can develop suitable strategies for the implementation of service robots in their stores.

2 Service Robots: A Literature Review

2.1 Differences Between Service Robots

Service robots differ from each other on at least three main characteristics (Wirtz et al., 2018). A first characteristic is their appearance: service robots can be physical (e.g. Pepper) or virtual (e.g. Siri). Second, service robots vary according to their level of anthropomorphism. They can be designed as humanoids (e.g. Sophia) or as non-humanoids (e.g. Kira). Thirdly, service robots can differ according to their capabilities. Some robots are designed and trained to perform cognitive-analytical processes (e.g. image analysis software assistants used in healthcare for medical diagnostics). Others are trained to engage in social interactions with humans (e.g. robotic shopping assistants that greet customers and assist them in finding products).

2.2 Differences Between Frontline Service Robots and Other AI Technologies

There are two main characteristics of frontline service robots which distinguish them from other AI technologies: their autonomy and their ability to interact with customers (Kiesler & Hinds, 2004; Wirtz et al., 2018). Frontline

service robots are capable of autonomous decision making based on the data they receive from their sensors, cameras, and microphones (Wirtz et al., 2018). They can, for example, monitor shelves, and look for products that are out of place (Bogue, 2019).

Another characteristic which distinguishes frontline service robots from other AI technologies is their ability to interact with customers; they are designed to create relationships with customers through their appearance (Van Doorn et al., 2017). In this regard, frontline service robots can approach human beings in a personal way. Accordingly, it is essential for service robots to be 'embodied' (Wasen, 2010).

2.3 Factors that Inhibit Interaction with Service Robots

Several factors determine whether people are willing to interact with service robots. Studies show that some people try to avoid robots during service encounters because they are uncertain of how to interact with the robot (Barnett et al. 2014). Consumers who have no previous experience with robots show more uncertainty and negative feelings towards them (Buchner et al. 2013). As a consequence, customers' attitudes towards robots are expected to improve when they get familiar with human-robot service interactions (Savela et al., 2017). However, users' expectations about what service robots are capable of and users' perceptions about the robot's actual capacities after they have interacted with it, often don't match. This 'adaptation gap' is one of the main factors influencing people's attitudes towards robots (Komatsu et al., 2012). When users have too high expectations about the robot, they will be disappointed with its service quality and stop the interaction. However, if the robot's performance exceeds users' expectations, customers will be more satisfied with the provided service and will continue to use it (Komatsu et al., 2012).

Moreover, service robots' social capabilities considerably influence users' attitudes towards interaction with them (Lu et al., 2020). The appearance of the robot also influences users' attitudes (Kiesler & Hinds, 2004; Wasen, 2010). People tend to have more positive attitudes towards robots when they resemble humans. Song (2017) emphasizes the importance of a physically attractive design in order to enhance retail customers' experiences.

Studies on human-robot interactions also discovered cultural differences in people' attitudes towards robots. Dekker et al. (2017), for example, found that people from developed countries think more positively about robot implementation. Bartneck et al. (2007) compared people's attitudes towards robots in seven different countries (China, Germany, Japan, Mexico, the Netherlands, the UK and the USA). Participants from the USA held the most positive attitudes towards

robots, especially regarding the aspect of interacting with them, while participants from Mexico were the most negative towards robots.

Finally, the literature shows that sociodemographic characteristics play a relevant role in people's attitudes towards and or willingness to interact with service robots. A first factor is one's educational level: highly educated people feel less anxious about robots and, therefore, focus more on the possible benefits that (service) robots can deliver (Onorato, 2018). Age is also a decisive factor. Elderly people are often less familiar with new technologies and, therefore, foster more negative attitudes towards robots (Hudson et al., 2017; Onorato, 2018). Song et al. (2016), for example, found that older patients try to avoid contact with robot nurses, whereas Pulido et al. (2017) found that children interact very easily with robots during physical rehabilitation sessions. In an experimental study by Fernandez-Llamas et al. (2018), primary school children even preferred a robot over a human teacher. In addition, the literature shows that people's attitudes towards robots is gender-specific (Ivanov et al., 2018; Belanche et al., 2020). In general, women hold more negative attitudes towards robots than men (Chen & Huang, 2016).

2.4 Service robots in the retail sector

There are only a few studies on the effectiveness of service robots in the retail sector (Belanche et al., 2020). Moreover, studies on customer interaction with robots mostly focused on virtual shop assistants such as chatbots (Pantano & Pizzi, 2020). Bogue (2019) is one of the few studies describing the functionality and benefits of service robots in retail shops.

The implementation of service robots in service activity settings can help overcome problems related to interpersonal service encounters. Firstly, personality and mood factors which may negatively affect service quality, are eliminated when a customer interacts with a robot instead of a human employee. Secondly, the problem of staff allocation due to fluctuations in product demand is solved. Also from the perceived benefits perspective, customers are likely to continue using the 'robot' service if the perceived service benefits outweigh the perceived risks and if other alternatives are considered as less beneficial (Bogue, 2019; Kim et al., 2021). Therefore, the service quality offered by service robot encounters should increase customers' perceived benefits of service robots and, subsequently, their adoption of this new technology. Moreover, a high service quality experience should improve positive attitudes towards robots and reduce the perceived risks of using this relatively new technology (cf. Lee, 2009).

Despite the ubiquitous use of robots in many domains, empirical research on the service quality of customer-robot interactions in retail environments is scant (Belanche et al., 2020). Recent studies focused on service robots in healthcare, the hospitality industry, and in financial institutions. This study fills that research gap by comparing customers' perceived service quality (PSQ) of a human-robot interaction and a human-human interaction in a retail setting. Based on the literature review, we propose the following hypothesis.

- H1: There is a statistically significant difference between consumers' perceived service quality (PSQ) of a human-human service encounter and a human-robot service encounter.

Based on previous research, we also examined the moderating role of consumers' attitudes towards robots, their age, their gender and their educational level on the relationship between type of service assistant (human versus robot) and consumers' PSQ-scores. Therefore, the corresponding hypotheses are as follows.

- H2: Consumers' attitudes towards robots moderate the relation between type of service assistant and PSQ-scores.
- H3: Consumers' gender, age, and educational level moderate the relation between type of service assistant and PSQ.

Managers who want to implement service robots in their retail shops, must know if consumers prefer being served by a human employee or a service robot, and whether this preference depends on consumers' attitudes towards robots and sociodemographic characteristics. This led to the following hypothesis.

- H4: Consumers' preferences for a human or a robot service encounter depend on the perceived service quality of the human-human interaction, the perceived service quality of the human-robot interaction, their positive attitudes towards robots and their age, gender, and educational level.

In order to test the hypotheses, a repeated measures design was used. This research design entails exposure of each participant to both experimental conditions (i.e. the human-robot service encounter and the human-human service encounter). Furthermore, participants' attitudes towards robots (H2) and the measured socio-demographic variables (H3) were exactly the same in both conditions. Besides, a repeated measures design makes it possible to compare participants' preferences for both retail settings and, therefore,
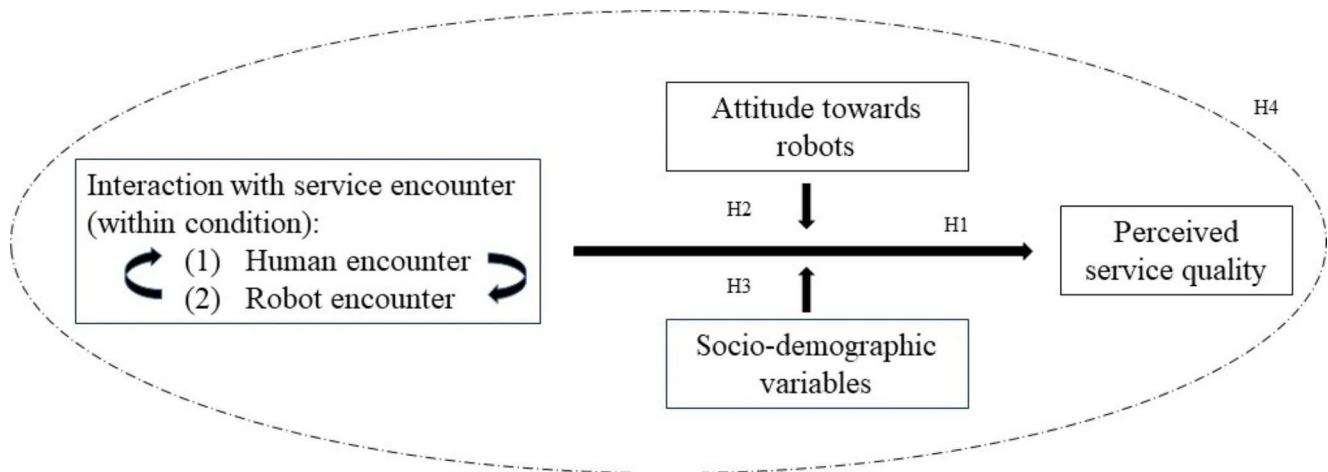
Fig. 1 Research design of the interaction with service encounter

Fig. 2 Illustrations of the scenarios: on the left the human-human interaction scenario and on the right the human-robot scenario

test H4. In Fig. 1 an overview of the research design is presented.

3 Methods

3.1 Participants

We collected data of 537 participants using Qualtrics and Prolific Academic. Data from the same IP address, and data from participants who did not complete the questionnaire or who had completed the questionnaire in less than 6 min were not included in the analyses. These procedures left 425 participants in our total sample. 57.6% of the participants were male. Participants' ages ranged from 18 to 70 years (M = 30.85 years, SD = 8.6 years). At the time of the survey 29% of the participants held a master's degree, 35.3% a bachelor's degree, 11.7% a high school degree, and 24% represented other levels of education. Almost all participants (99.96%) were a citizen of a country inside the EU.

3.2 Materials

To compare participants' perceived service quality of both retail encounters, two scenarios were created: a retail scenario in a shoe shop with a human encounter and a retail scenario with a robot encounter. In both scenarios participants were asked to imagine that they experienced the respective shopping encounter. Each scenario also contained four pictures (see Fig. 2) that facilitated participants in imagining the described customer experience. This technique helps to get more natural and real insights related to the study subject in comparison with other design ideation methods (Tiberius et al., 2020). For the robot-encounter-scenario, illustrations of the humanoid robot Pepper were chosen. Screenshots of the illustrations of the two scenarios are shown in Fig. 2.

The illustrations were added to a description of the shopping experience. Figure 3 contains the description of the scenario of the robot encounter.
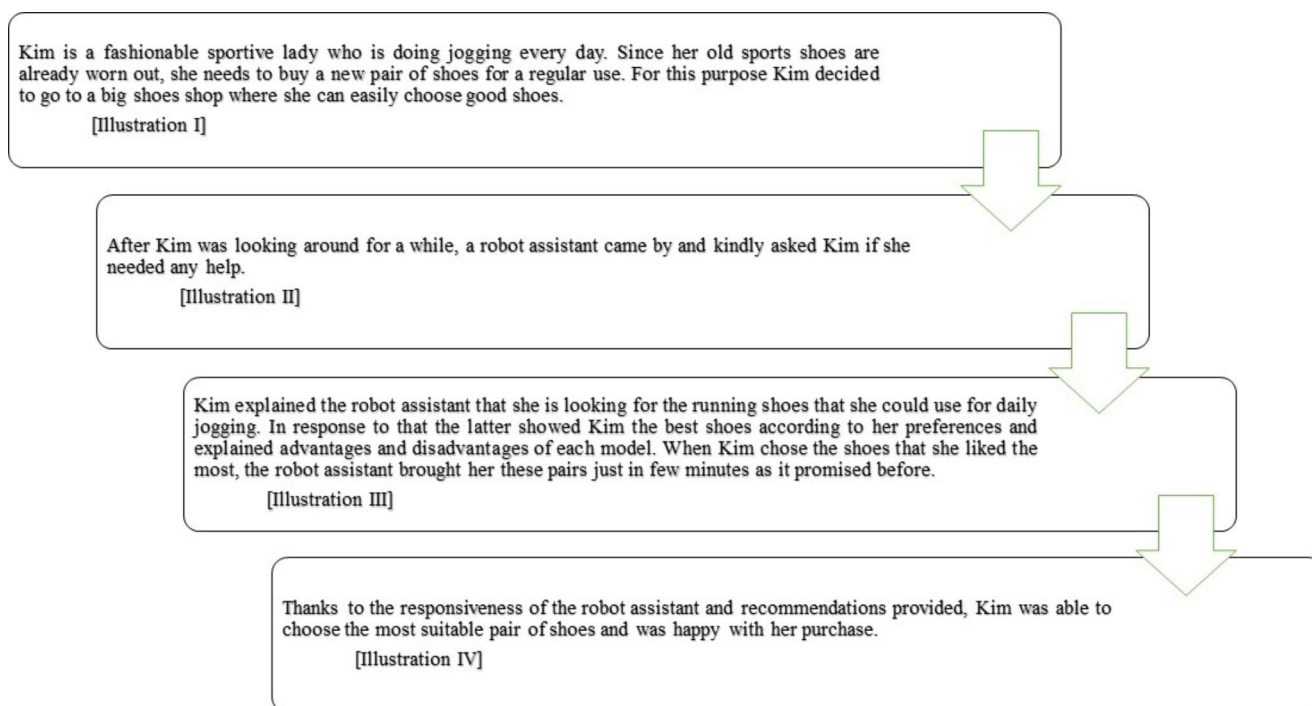
Kim is a fashionable sportive lady who is doing jogging every day. Since her old sports shoes are already worn out, she needs to buy a new pair of shoes for a regular use. For this purpose Kim decided to go to a big shoes shop where she can easily choose good shoes.

[Illustration I]

After Kim was looking around for a while, a robot assistant came by and kindly asked Kim if she needed any help.

[Illustration II]

Kim explained the robot assistant that she is looking for the running shoes that she could use for daily jogging. In response to that the latter showed Kim the best shoes according to her preferences and explained advantages and disadvantages of each model. When Kim chose the shoes that she liked the most, the robot assistant brought her these pairs just in few minutes as it promised before.

[Illustration III]

Thanks to the responsiveness of the robot assistant and recommendations provided, Kim was able to choose the most suitable pair of shoes and was happy with her purchase.

[Illustration IV]

Fig. 3 Scenario of the hypothetical shopping experience in the human-robot interaction condition

Nowadays service robots are replacing human employees in many domains as they are able to perform tasks more effectively. As one can guess, service robots are designed to interact with humans in a natural, interpersonal manner. Currently the most widely used service robot is called Pepper which you can see on the picture

Fig. 4 Introduction to service robots

3.3 Procedure

We used a between subjects-design: each participant evaluated both shopping experiences which were integrated as scenarios in an online survey. Participants had to complete a captcha task before starting the survey. Since participants might not be familiar with the term 'service robots', we added a description (see Fig. 4) at the beginning of the questionnaire.

First, we measured participants' attitudes towards robots on a 14-items-7-point Likert scale based on Nomura's et al.'s (2006) Negative Attitudes Toward Robots Scale (NARS). The items cover three different dimensions including people's attitudes towards (1) interactions with robots (6 items), (2) the social influence of robots (5 items), and (3) emotions in interactions with robots (3 items). We recoded participants' answers to the scale items, such that a high mean score on the 14 items signifies a positive attitude towards robots.

Next, we presented one of the two scenarios to the participants. Directly after they had read the scenario, we asked the participants to evaluate the 'overall quality of the shop experience' on a 7-point semantic differential scale (cf. Cronin and Taylor, 1992): *Based on this scenario the overall service quality is very poor/excellent*. Next, participants' perceived service quality of the service encounter (based on the SERVPERF model) was measured. We used a 22-items-7-points Likert scale based on Cronin and Taylor's (1992)

Table 1 *Description of the measurement instruments (N = 425)*

Construct	Mean	SD	Items	Cronbach's alpha	Kurtosis	Skewness
Attitudes towards robots	4.47	1.04	14	0.85	− 0.395	− 0.147
PSQ Human	5.83	0.79	29	0.96	− 0.437	− 0.546
PSQ Robot	5.58	0.89	29	0.94	− 0.459	− 0.445

five dimensional scale: tangibility (4 items), reliability (5 items), responsiveness (4 items), assurance (4 items), and empathy (5 items). In addition, we included two extra dimensions: usefulness (3 items, based on Davis, 1989) and satisfaction (4 items, based on Landrum et al., 2007). Subsequently, participants were shown the other scenario and answered the same questions. To avoid order-effects, the two scenarios were presented in a random order. 206 participants (48.5%) were first shown the scenario with the human-robot encounter, whereas 219 participants (51.5%) were first given the human-human encounter scenario.

After the participants had answered the service quality items for both scenarios, we asked them to indicate which service experience scenario they preferred (the human-robot interaction or the human-human interaction). Finally, socio-demographic variables (educational level, age, gender and place of residence) of the participants were measured.

After the data were collected, Cronbach's alpha reliability analyses were used to calculate the internal consistency of the three constructs: general attitudes towards robots, perceived service quality of the human-human encounter (PSQ Human) and perceived service quality of the human-robot encounter (PSQ Robot). Table 1 shows that all constructs exhibited a Cronbach's alpha value of 0.85 or above, and that the Kurtosis and Skewness scores of the different variables were acceptable (scores between − 1 and + 1). Hence, data distribution was roughly symmetric and values did not deviate from a normal distribution (Ghazali et al., 2020).

Furthermore, independent t-tests showed that the order in which both scenarios were presented did not statistically significantly influence participants' average PSQ scores for the human-human encounter ($t(423) = 0.718$; $p = .473$), nor for the human-robot encounter ($t(423) = 0.648$; $p = .517$).

4 Research Results

First, we analysed whether participants' perceived service quality scores for the human-human service encounter statistically significantly differed from their perceived service quality scores for the human-robot service encounter (H1). A within-subjects ANOVA was carried out with 'type of encounter' (robot versus human) as the within-subjects factor. The results of the analysis showed a statistically significant difference between the mean scores of the perceived service quality scales for both service encounters: $F(1,$

Table 2 *Average scores of perceived service quality broken down by type of encounter and participants' general attitudes towards robots*

Encounter	Attitudes towards robots	Average PSQ	SD	N
Human	Relatively low	5.69	0.96	196
	Relatively high	5.95	0.78	229
Robot	Relatively low	5.24	1.01	196
	Relatively high	5.87	0.83	229
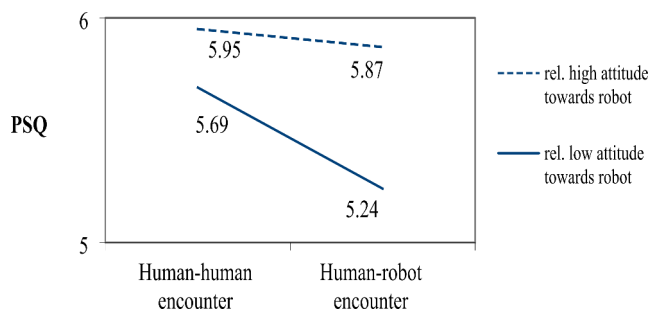
Fig. 5 Visualization of the interaction effect between participants' general attitudes towards robots and their PSQ scores of the human-human and the human-robot encounter

$424) = 32.47$, $p < .001$. The average PSQ score for the human-human service encounter scenario ($M = 5.82$, $SD = 0.88$) was statistically significantly higher than the average score for the human-robot encounter scenario ($M = 5.58$, $SD = 0.97$). Therefore, the first hypothesis was accepted.

Next, we examined whether participant's attitudes towards robots moderate the relation between type of service encounter and their perceptions of service quality (H2), using a mixed-design ANOVA. The type of encounter (human versus robot) was used as a within-subjects factor, whereas participants' general attitudes towards robots were added as a between-subjects factor. Based on their scores on the general attitudes towards robots scale our sample was divided into two groups by a median split: a group with relatively high positive attitudes towards robots (scores of 4.38 and above) and a group with relatively low positive attitudes towards robots (scores of 4.37 and below). Table 2 presents the average scores for the different groups (human versus robot encounter and low versus high positive attitudes towards robots).

A 2 (human-human versus human-robot service encounter) x 2 (low versus high positive attitudes towards robots) mixed-model ANOVA revealed a statistically significant main effect of the within-subjects factor 'type of encounter' ($F(1, 423) = 37.42$, $p < .001$) and the between-subjects

Table 3 *Descriptive statistics for the seven PSQ dimensions*

PSQ dimensions (# items, α-score human encounter, α-score robot encounter)	Human encounter M (SD)	Robot encounter M (SD)	Repeated analyses F (1, 424) (p-value)	95% CI
PSQ Reliability (3, 0.88, 0.86)	6.26 (0.92)	6.12 (1.02)	10.887 (0.001)	[0.055; 0.217]
PSQ Responsiveness (4, 0.66, 0.62)	5.39 (1.05)	5.30 (1.07)	3.104 (0.079)	[-0.010; 0.184]
PSQ Assurance (4, 0.84, 0.80)	5.56 (1.12)	5.11 (1.21)	43.665 (<0.001)	[0.315; 0.582]
PSQ Empathy (3, 0.88, 0.84)	5.61 (1.40)	5.33 (1.45)	16.836 (<0.001)	[0.148; 0.419]
PSQ Satisfaction (4; 0.91, 0.93)	6.14 (0.96)	5.81 (1.22)	31.475 (<0.001)	[0.212; 0.442]
PSQ Usefulness (3, 0.88, 0.89)	5.95 (1.07)	5.68 (1.24)	15.305 (<0.001)	[0.128; 0.387]
PSQ Tangibility [1] (2, 0.53 **, 0.60 **)	6.15 (0.97)	5.98 (1.13)	10.405 (0.001)	[0.067; 0.276]

[1] For the 2 items measuring *tangibility* a correlation coefficient was measured instead of Cronbach's alpha (** $p < .001$)

factor 'general attitudes towards robots' ($F (1, 423) = 35.43$, $p < .001$).

Figure 5 visualizes the statistically significant difference between the perceived service quality scores of both service encounters, in combination with participants' general attitudes towards robots. We found no statistically significant differences between both service encounters ($M_{Human} = 5.95$ and $M_{Robot} = 5.87$) regarding perceived service quality for participants with relatively high positive attitudes towards robots ($t(228) = 1.814$; $p = .071$), whereas participants with relatively low positive attitudes towards robots held statistically significantly lower perceptions of service quality ($t(195) = 5.820$, $p < .001$) for the robot encounter compared to the human encounter ($M_{Human} = 5.69$ and $M_{Robot} = 5.24$).

Especially, the gap between the average PSQ scores for the human-robot encounter differed statistically significantly between the group with relative low ($M = 5.24$) and the group with relative high positive attitudes towards robots ($M = 5.87$): $t(423) = 7.07$, $p < .001$. However, Fig. 5 also shows that participants with relatively low positive attitudes towards robots held statistically significantly lower ($t(423) = 3.11$, $p = .002$) perceived service quality scores for the human-human service encounter ($M = 5.69$) compared to participants with relatively high positive attitudes towards robots ($M = 5.95$).

Furthermore, we checked whether the differences found for the aggregated PSQ scale also hold for each of the seven service quality dimensions. In Table 3 the average scores for both types of service encounters for each of the seven PSQ dimensions are presented.

The scores for the separate PSQ dimensions also differed statistically significantly for the human and for the robot service encounter (see Table 4). The repeated analyses show that for almost all seven dimensions the obtained average scores for the human service encounter were statistically significantly higher compared to the PSQ scores for the robot service encounter (only for 'responsiveness' the difference was not statistically significant). The differences between the perception scores are particularly large for the following dimensions: 'assurance', 'satisfaction', 'empathy' and 'usefulness'.

Next, we checked the moderating role of participants' attitudes towards robots for each PSQ dimension using a mixed-design ANOVA model. Table 4 shows that the average scores on all PSQ dimensions differed statistically significantly between both types of service encounters for the participants with relatively low positive attitudes towards robots. However, for participants with relatively high positive attitudes towards robots, only the scores for the dimension 'assurance' were statistically significantly higher for the human-human service encounter scenario compared to the human-robot service encounter scenario. Based on these results we can accept our second hypothesis.

{insert Table 4 about here}

Table 4 *Average score on the seven PSQ dimensions for participants with relative low positive attitudes towards robots versus participants with relatively high positive attitudes towards robots*)

PSQ dimensions	Low positive attitudes towards robots			High positive attitudes towards robots		
	PSQ Human	PSQ Robot	95% CI	PSQ Human	PSQ Robot	95% CI
PSQ Reliability	6.13 (1.04)*)	5.84 (1.17)	[0.145; 0.433]	6.37 (1.17)	6.37 (0.79)	[-0.079; 0.087]
PSQ Responsiveness	5.27 (1.09)	5.03 (107)	[0.095; 0.382]	5.49 (1.01)	5.53 (1.02)	[-0.173; 0.088]
PSQ Assurance	5.41 (1.18)	4.78 (1.25)	[0.409; 0.861]	5.68 (1.05)	5.39 (1.10)	[0.136; 0.443]
PSQ Empathy	5.42 (1.50)	4.95 (1.47)	[0.237; 0.695]	5.77 (1.29)	5.64 (1.36)	[-0.030; 0.283]
PSQ Satisfaction	6.02 (1.02)	5.40 (1.35)	[0.419; 0.824]	6.24 (0.90)	6.16 (0.95)	[-0.040; 0.190]
PSQ Usefulness	5.77 (1.16)	5.30 (1.33)	[0.248; 0.688]	6.10 (0.97)	6.02 (1.06)	[-0.069; 0.223]
PSQ Tangibility	6.04 (1.04)	5.68 (1.25)	[0.184; 0.535]	6.24 (0.90)	6.23 (0.94)	[-0.110; 0.131]

* underlined numbers indicate a statistically significant difference in PSQ scores ($p < .05$) between the human-human and the human-robot encounter condition within the group with relatively low positive attitudes towards robots and the group with relatively high positive attitudes towards robots respectively

Table 5 *Effects of explanatory variables on preference for a human encounter in a retail environment*

Variables (X_i)	Estimated Coefficients (β)		Exp (B)	p-value	95% CI for Exp (B) [lower; upper]
PSQ Human	2.502	**	12.208	< 0.01	[5.596; 26.633]
PSQ Robot	-2.160	**	0.115	< 0.01	[0.053; 0.252]
Average attitude towards robots	– 0.879	**	0.415	< 0.01	[0.275; 0.628]
Gender (male)	– 0.352		0.703	0.306	[0.359; 1.379]
Age	– 0.019		0.981	0.337	[0.944; 1.020]
Education	– 0.049		0.952	0.886	[0.484; 1.871]
Constant	4.097	*	60.160	0.011	
Log likelihood (estimated model)			244.966		
Omnibus Tests of Model Coefficients			X^2 [6] = 114.518 ($p < .001$)		
R² Nagelkerke			0.454		
Hosmer & Lemeshow Goodness of Fit			X^2 [8] = 3.074 ($p = .930$)		
U² (% predicted correctly)			81.3%		

**significant ($p < .01$), *significant ($p < .05$)

For our third hypothesis we analysed whether participants' gender, age and educational level statistically significantly moderate the effect of service interaction type (human-human versus human-robot) on participants' perceived quality of the service encounter. A mixed-design ANOVA showed no statistically significant interaction-effect for gender ($F(1, 423) = 0.354$; $p = .552$): both men and women evaluated the human-human service encounter statistically significantly higher than the human-robot encounter. Furthermore, no statistically significant interaction effect was found for age ($F(1,421) = 1.253$; $p = .264$), nor for educational level (university degree versus no-university degree): $F (1, 296) = 0.026$; $p = .871$. In addition, we analysed whether the socio-demographic characteristics gender, age and educational level interact with participants' attitudes towards service robots. This was not the case. All p-values showed that the moderators had no statistically significant influence on the tested relationship. Therefore, we could not accept our third hypothesis that sociodemographic variables moderate the relationship between type of service assistant and perceived service quality scores.

To test our fourth hypothesis, we analysed the distribution of our participants' preferences for the human-human and the human-robot interaction. The number of participants who opted for a human-assisted shopping experience was statistically significantly higher (70.6%) compared to the number of participants that preferred the shopping

Table 6 *Classification of correctly predicted preferences*

		Predicted		
		Choice encounter		Percentage correct
Observed		Human	Robot	
Choice encounter	Human	49	37	57.0
	Robot	19	195	91.1
Overall percentage				81.3

The cut-value is 0.500

experience with the service robot (29.4%). Next, we used a binomial logit model to estimate to what extend participants' PSQ scores for both interaction types and their attitudes towards robots influence their preference for the shopping experience. Sociodemographic variables (age, gender, educational level) were also entered in the model. The probabilities that a participant chooses for the robot encounter or the human encounter are given by:

$$P_{Robot}(X_i, \omega) = \frac{\exp(X_t^t \beta)}{1 + \exp(X_t^t \beta)} \quad (1)$$

$$P_{Human}(X_i, \omega) = 1 - P_{EF}(X_i, \omega) = \frac{1}{1 + \exp(X_t^t \beta)} \quad (2)$$

in which ω is a vector of the estimated coefficients β, and X_i are the regressor variables in the model. In Table 5 the estimated coefficients, standard errors and fit values of the model are presented.

The probability that participants have a preference for the human encounter statistically significantly increases when their PSQ scores for the human encounter are higher, and their attitudes towards robots and PSQ scores for the robot encounter are lower. Furthermore, the results indicate that participants' gender, educational level and their age do not statistically significantly influence their preference for a human encounter ($p > .05$). The direction of the estimated coefficients matches previous findings. The different goodness of fit values are satisfying, and indicate that the model is statistically significantly better than the null model. Finally, Table 6 shows how many cases were correctly predicted in the full binomial logit model, using a cut-value of 0.500. The overall percentage of cases that were correctly predicted is 81.3% (91.1% for the human-human encounter and 57.0% for the human-robot encounter). Based on these findings, we can accept our last hypothesis.

5 Conclusions and Discussions

Due to the rapid evolution of technologies, companies tend to replace human employees with service robots in numerous domains, including the retail industry which is considered to

be one of the most appealing sectors for robot deployment (Robotic Industries Association, 2017). However, it is still unclear how retail customers react to service encounters with frontline service robots. Our study compared customers' evaluations of a service provided by a frontline service robot with their evaluations of the same service provided by a human shop assistant. Furthermore, we examined the moderating role of customers' general attitudes towards robots and three socio-demographic characteristics (i.e. age, gender and educational level) on the relationship between type of service interaction (human-human versus human-robot) and customers' perceptions of the offered service quality.

We found that the perceived service quality of the human-human service encounter was evaluated statistically significantly higher compared to the human-robot service interaction. We also found that the number of respondents who preferred the human shop assistant was almost three times higher than the number of participants who preferred the service robot. This result suggests that customers prefer human service employees over service robots for their shopping experiences. This finding is consistent with previous studies (Mende et al., 2019). However, when we took participants' general attitudes towards robots into account, participants with relatively low positive attitudes towards robots expressed lower positive perceptions of the human-robot service encounter compared to the human-human service encounter. For participants with relatively high positive attitudes towards robots, PSQ scores for the human-human service interaction and PSQ scores for the human-robot interaction did not statistically significantly differ. Furthermore, our findings showed the same pattern for each dimension of the PSQ scale. Statistically significant differences between both types of encounters were found for 'reliability', 'assurance', 'empathy', 'satisfaction', 'tangibility', 'responsiveness' and 'usefulness' for participants with relatively low positive attitudes towards robots, whereas almost no statistically significant differences were found for participants with relative high positive attitudes towards robots.

In order to identify other factors that play an important role in human-robot service encounters, we looked into the moderating effect of the following socio-demographics characteristics: age, gender and educational level. However, the effect of type of service encounter on participants' perceived quality of the provided service did not differ statistically significantly according to their gender, educational level and age. With regard to the existing literature, these results can be characterized as ambiguous as they support some research (e.g., Nomura 2014), while contradicting others (Chen & Huang, 2016).

Finally, we found that participants' preference for the human-human encounter was statistically significantly and positively influenced by their general attitudes towards robots and their PSQ scores for the human-human encounter, and statistically significantly and negatively influenced by their PSQ scores for the human-robot encounter. Furthermore, our study showed that neither age, gender nor educational level affected participants' preferences for a human-human or a human-robot encounter.

5.1 Managerial implications

This study offers valuable findings for companies that are currently using or planning to deploy frontline service robots to assist their customers. These companies should focus on the improvement of customers' general attitudes towards robots, for example, by increasing interaction facilities such as touching and/or talking to the service robot. In this way, unpleasant feelings such as fear or stress can be reduced in older customers or customers with little experience in using robots. Our findings also provide important insights for retail owners and marketing managers, as they will be able to develop more tailored strategies for service encounters, and thus improve the effectiveness of interactions between customers and sales personnel (both human and robot). This study further demonstrates that customers with relatively low positive attitudes towards robots score statistically significantly lower on all dimensions of the PSQ scale. Therefore, companies should focus on all aspects of service quality to stimulate the acceptance rate of robot encounters in a retail environment.

5.2 Limitations and suggestions for future research

Even though this research extends our knowledge of human-robot interactions in retail settings, it is subject to a number of limitations that could be addressed in further research. First of all, this research is a scenario-based experiment, which reduces the level of generalizability of our findings to more real-world situations. Therefore, a similar experiment should be conducted in a brick-and-mortar store. The use of video format scenarios instead of a combination of text and illustrations is another possibility to extend our findings. However, it is difficult to set up two identical video based scenarios of a human-robot interaction and a human-human interaction in a similar retail setting. Second, our study was limited to one service robot: the humanoid robot Pepper. The study was also limited to one retail setting: a shoe store. Other types of robots (non-humanoid, virtual-tele-presence, zoomorphic), other retail shops (clothing, sport apparel, groceries) and industries (hospitality, entertainment, finance) are also interesting and relevant to investigate in order to determine whether our findings can be generalised. Furthermore, the use of delivery robots has been skyrocketing

since the pandemic (Hawkins 2021). Future research should analyse customers' PSQ of these types of robots. Third, the scenarios in our study were built around a middle-aged female customer. Although participants' age and gender did not affect their perceptions of service quality, other customer profiles should be included to match the socio-demographic parameters of the scenario character with those of the participant. Fourth, we investigated the moderating role of people's general attitudes towards robots on the relationship between type of interaction and PSQ. Further research might focus on other factors such as customers' (negative) experiences with service robots. Lee et al. (2010) found that a breakdown in a robotic service (i.e. bringing the wrong soda drink) had a negative effect on service satisfaction. The study further showed that the effectiveness of different recovery strategies depends on customers' service orientation. Participants with a 'relational orientation' responded better to an apology by the service robot, whereas participants with a more 'utilitarian orientation' responded better to a financial compensation ('drink is for free').

Researchers could also use other constructs to measure the outcome of the service encounter (e.g., willingness to buy/use the brand's products, desire to recommend the retail brand to a friend, or revisit intentions). Next, we examined participants' perceptions at a given point in time. As customers become more familiar with service robots, their attitudes towards robots and service quality perceptions may evolve. Therefore, future research could apply a longitudinal approach to obtain more exhaustive results about changing customers' perceptions of the added value provided by a service robot. Finally, the COVID-19 pandemic has statistically significantly increased the level of robot deployment due to safety measures (Kim et al., 2021). The data collection took place during the pandemic (January 2021). During the pandemic people more often interacted with robots and/ or were willing to accept them for their service encounters (Talk and Lew 2020). Hence, there is a need for further research on how people's perceptions and attitudes towards service robots will evolve in the post-pandemic period.

Declarations

7. References

Barnett W, Foos A, Gruber T, Keeling D, Keeling K, Nasr L (2014) August 25–29). *Consumer perceptions of interactive service robots: A value-dominant logic perspective*. The 23rd IEEE International Symposium on Robot and Human Interactive Communication [Paper presentation]. Edinburgh, UK. DOI: https://doi.org/10.1109/ROMAN.2014.6926404

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

Belanche D, Casaló LV, Flavián C, Schepers J (2020) Service robot implementation: a theoretical framework and research agenda. Serv Ind J 40(3–4):203–225

Bogue R (2019) Strong prospects for robots in retail. The Industrial Robot 46(3):326–331

Buchner R, Wurhofer D, Weiss A, Tscheligi M (2013) Robots in time: How user experience in human-robot interaction changes over time. In G. Herrmann, M.J. Pearson, A. Lenz, P. Bremner, A. Spiers, & U. Leonards (Eds.), S*ocial Robotics ICSR 2013 Lecture Notes in Computer Science* (vol. 8239, pp. 138–147). DOI: https://doi.org/10.1007/978-3-319-02675-6_14

Chen NH, Huang SCT (2016) Domestic technology adoption: comparison of innovation adoption models and moderators. Hum Factors Ergon Manuf Serv Ind 26(2):177–190

Cronin JJ Jr, Taylor SA (1992) Measuring service quality: a re-examination and extension. J Mark 56(3):55–68

Davis F (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 13(3):319–340

Dekker F, Salomons A, van der Waal J (2017) Fear of robots at work: the role of economic self-interest. Socio-Economic Rev 15(3):539–562

Fernandez-Llamas C, Conde MA, Rodríguez-Lera FJ, Rodríguez-Sedano FJ, García F (2018) May I teach you? Students' behavior when lectured by robotic vs. human teachers. Comput Hum Behav 80:460–469

Ghazali AS, Ham J, Barakova E, Markopoulos P (2020) Persuasive Robots Acceptance Model (PRAM): roles of social responses within the Acceptance Model of Persuasive Robots. Int J Social Robot 12:1075–1092

Grewal D, Kroschke M, Mende M, Roggeveen AL, Scott ML (2020) Frontline cyborgs at your service: how human enhancement technologies affect customer experiences in retail, sales and service settings. J Interact Mark 51:9–25

Hawkins A (2021) Grubhub will use Russian-made robots to deliver food on college campuses. Roving lunchboxes on wheels. Retrieved from https://www.theverge.com/2021/7/7/22566652/grubhub-delivery-robot-yandex-college-campus-autonomous

Hudson J, Orviska M, Hunady J (2017) People's attitudes to robots in caring for the elderly. Int J Social Robot 9:199–210

Hullinger J (2016), February 16 What the Lowe's robot will do for you – and the future of retail. *Fast company*. Retrieved from https://www.fastcompany.com/3056640/what-the-lowes-robot-will-do-for-you-and-the-future-of-retail

International Federation of Robotics (2020) *Service robots record: Sales worldwide up 32%.* Retrieved from https://ifr.org/ifr-press-releases/news/service-robots-record-sales-worldwide-up-32

Ivanov S, Webster C, Garenko A (2018) Young russian adults' attitudes towards the potential use of robots in hotels. Technol Soc 55:24–32

Kiesler S, Hinds P (2004) Introduction to this special issue on Human-Robot Interaction. Human–Computer Interact 19(1–2):1–8

Kim S, Kim J, Badu-Baiden F, Giroux M, Choi Y (2021) Preference for Robot Service or Human Service in Hotels? Impacts of the COVID-19 pandemic. Int J Hospitality Manage 93:102795

Komatsu T, Kurosawa R, Yamada S (2012) How does the difference between users' expectations and perceptions about a robotic agent affect their behavior? Int J Social Robot 4(2):109–116

Landrum H, Prybutok VR, Zhang X (2007) A comparison of Magal's service quality instrument with SERVPERF. Inf Manag 44(1):104–113

Lee MC (2009) Factors influencing the adoption of internet banking: an integration of TAM and TPB with perceived risk and perceived benefit. Electron Commer Res Appl 8(3):130–141

Lee MK, Kielser S, Forlizzi J, Srinivasa S, Rybski P(2010) Gracefully mitigating breakdowns in robotic services. *5th ACM/IEEE International Conference on Human-robot Interaction* (pp. 203–2010). IEEE. doi: 10. 1109/HRI.2010.5453195

Lu VN, Wirtz J, Kunz W, Paluch S, Gruber T, Martins A, Patterson P (2020) Service robots, customers, and service employees: what can we learn from the academic literature and where are the gaps? J Service Theory Pract 30(3):361–391

Mende M, Scott ML, van Doorn J, Shanks I, Grewal D (2019) Service robots rising: how humanoid robots influence service experiences and food consumption. J Mark Res 56(4):535–556

Nomura T(2014) Influences of experiences of robots into negative attitudes toward robots. *The 23rd IEEE International Symposium on Robot and Human Interactive Communication* (pp. 460–464). doi: https://doi.org/10.1109/ROMAN.2014.6926295

Nomura T, Suzuki T, Kanda T, Kato K (2006) Measurement of negative attitudes toward robots. Interact Studies: Social Behav Communication Biol Artif Syst 7(3):437–454

Onorato DA (2018) Robots, unions, and aging: determinants of robot adoption evidence from OECD countries. Atl Economic J 46(4):473–474

Pantano E, Pizzi G (2020) Forecasting artificial intelligence on online customer assistance:evidence from chatbot patents analysis. J Retailing Consumer Serv 55:102096

Pulido JC, González JC, Suárez-Mejías C, Bandera A, Bustos P, Fernández F (2017) Evaluating the child-robot interaction of the NAOtherapist platform in pediatric rehabilitation. Int J Social Robot 9(3):343–358

Robotic Industries Association (2017), December 26 *Robots in retail stores are making a big impact*. Retrieved from: https://www.robotics.org/blog-article.cfm/Robots-in-Retail-Stores-are-Making-a-Big-Impact/76

Robots.net. *What are service robots and how they benefit mankind?* Retrieved from: https://robots.net/tech-reviews/what-are-service-robots/

Savela N, Turja T, Oksanen A (2017) Social acceptance of robots in different occupational fields: a systematic literature review. Int J Social Robot 10(4):493–502

SoftBank Robotics (n.d.). *Pepper*. Retrieved February 19, 2021, from https://www.softbankrobotics.com/emea/en/pepper

Song A, Wu C, Ni D, Li H, Qin H (2016) One-therapist to three-patient telerehabilitation robot system for the upper limb after stroke. Int J Social Robot 8(2):319–329

Song SY(2017) *Modeling the consumer acceptance of retail service robots* [Doctoral dissertation, University of Tenessee]. Tennessee Research and Creative Exchange. https://trace.tennessee.edu/utk_graddiss/4655

Talk B, Lew E(2020), May 5 *Pandemic and the smarter world: A future of robots*? Columbia Business School, Ideas and Insights. Retrieved from https://www8.gsb.columbia.edu/articles/brand-talk/pandemic-and-smarter-world-future-robots

Tiberius V, Siglow C, Sendra-García J (2020) Scenarios in business and management: the current stock and research opportunities. J Bus Res 121:235–242

Van Doorn J, Mende M, Nobble SM, Hulland J, Ostrom AL, Grewal D, Petersen JA (2017) Domo Arigato Mr. Roboto: emergence of automated social presence in organizational frontlines and customers' service experiences. J Service Res 20(1):43–58

Wasen K (2010) Replacement of highly educated surgical assistants by robot technology in working life: paradigm shift in the service sector. Int J Social Robot 2(4):431–438

Wirtz J, Patterson PG, Kunz WH, Gruber T, Lu VN, Paluch S, Martins A (2018) Brave new world: service robots in the frontline. J Service Manage 29(5):907–931