Service Sector Professionals' Perspective on Robots Doing Their Job in the Future

Nina Savela[0000-0002-7042-6889], Rita Latikka[0000-0003-3798-0017], Reetta Oksa[0000-0002-8007-4653] and Atte Oksanen[0000-0003-4143-5580]

Tampere University, Faculty of Social Sciences, Kalevantie 5, 33014 Tampere, Finland
nina.savela@tuni.fi

Abstract. After a long history of industrial automation, robots are entering service fields at an accelerating rate due to the recent technological advances in robotics. Understanding the acceptance and applicability of robots is essential for successful introduction, desired benefits, and well-managed transformation of the labor market. In this work, we investigated whether service sector professionals consider robots applicable to their field compared to professionals from other sectors. We collected survey data from Finnish (N = 1817) and U.S. participants (N = 1740) and analyzed them using ordinary least squares regression. Results showed that Finnish and U.S. participants from the service sector disclosed a less positive attitude toward robots' suitability to their own occupational field compared to participants from other fields. Younger age, technological expertise, prior experience interacting with robots at work, and positive attitude toward robots were associated with perceived suitability. Perceived robot suitability was also found to mediate the relationship between occupational sector and positive interaction attitudes. The results indicate that robots entering into service industries evokes some resistance and doubt in professionals of these fields. Emerging generations and increasing technological knowledge and prior experience with robots at work are central factors when introducing robots in a socially sustainable way.

Keywords: robots, work, service sector, perceived suitability, social acceptance, attitudes

1 Introduction

After a long history of industrial robots and automation, robots are entering service fields at an accelerating rate due to the recent technological advances in robotics and are expected to revolutionize the service sector [1]. The service sector consists of multiple fields, such as health care and education, ranging from service production to customer interaction. Designing new technology for humans to use in new domains of work involves factors such as user acceptance and intention to use [2]. The people working in the field decide whether or not they prefer to use or interact with a new technology, which may remain unactualized despite the original intention or plan of other stakeholders. Therefore, understanding the acceptance and applicability of robots is essential for successful introduction, desired benefits, and well-managed transformation of the labor market.

The consumption and use of service robots is rising rapidly [3]. Robots can be classified as service robots and further to personal and professional service robots, referring to a device designed for professional or nonprofessional use that performs functions that are useful to human beings and that are outside the scope of industry [4]. Thus, a robot is defined by the specific domain it is designed for, but its appearance and level of automation can vary from a robotic device to a humanoid robot and from teleoperated to autonomous robots. To give a few examples, the humanoid robots NAO [5,6] and Pepper [7] were designed and optimized especially for human interaction. A telepresence robot, Double, is also intended to facilitate social interaction [8], and the more autonomous Paro is a seal-like robot designed to act as a therapeutic tool [9].

Designing robots for the service sector has raised some concerns among researchers and engineers regarding the successful interaction and acceptance of people with no technological expertise [10]. People have also been found to react unfavorably to working in close collaboration with robots instead of humans [11]. Previous studies comparing acceptance of robots in different jobs and life domains suggest that people could be more hesitant to accept and adapt robots in contexts in which close interaction with robots or creative abilities are required [12,13]. Hence, these domains are suspected to be more resistant to robot deployment, particularly when substituting humans.

Research on social acceptance of robots working in different occupational fields has focused more on health and social services during recent decades [14]. Care work professionals have been found to be receptive to robot work, for example in surgery [15,16,17]. A study regarding psychology students' willingness to adopt humanoid robots in their work field showed that they had a positive attitude toward using robots; however, they felt like they did not have the needed abilities to utilize robots [18]. Adaptability of robots to education has also generated some research interest. Researchers have found robots suitable for teaching domains such as children's education, engineering, and mathematics [19,20,21,22]. Also, in surveillance and military, robots have been found be accepted for dangerous tasks, such as search and rescue activities [23]. Similarly, also used for defense, drones are examples of robots flying in a confined space [24].

Apart from the service sector, robots and automation have been used for years for tasks such as lifting and assembling objects in the manufacturing industry. In addition, robots have been gradually adopted in other fields, such as in agriculture for assisting with milking activities [25]. Industrial robots are the largest category of robots outside the scope of service robots. Industrial robots include similar type of devices than service robots but are defined as industrial robots based on the context in which they are used. Other than industrial and service robots, there is a lack of specific categories of robots, because service robots are sometimes defined to include all robots used outside of industrial context. However, if categorized based on the specific service fields, robots outside of service sector could include professional service robots, such as delivery robots or robotic storage systems [26,27], and personal service robots in domestic use, such as vacuum cleaner robots [28]. Social acceptance of robots in occupational fields outside the service sector has been given far less attention in research [14].

Individual differences might also affect the acceptance of robots, but the results concerning sociodemographic factors have been mixed in previous studies. Some research teams have not found a statistically significant relationship between age and acceptance of robots [29,30], and those who have, have suggested that future researchers consider the prior experience in technology as a control to account for the variance it potentially produces [31,32]. Female gender has been found to be negatively connected to acceptance of robots [33,34], but this has also been criticized and instead suspected to derive from females' lower technological competence and less prior experience with robots [31]. Income has not been found to affect robot acceptance, although the research literature on this matter is scarce [35].

Introducing new technology such as advanced robots affects society more broadly. For this reason, researchers have requested a broader examination of acceptance of and resistance to robots in new domains beyond a customer- and user-centered research approach [36]. In addition to customers, it is valuable to consider the perspectives of professionals' and employees' from the fields because they are competing with robots for the jobs and they hold the unique human abilities that advanced technology is not yet able to offer in work life [37]. Professionals are also key players in innovation spread and technology innovation adoption [38,39] and are a valuable source of information regarding the applicable work domains that currently exist for robots and the current state of social acceptance of robots within these fields.

1.1 Perceived Suitability and Related Theories

Attitudes toward technology have previously been measured using the technology acceptance model (TAM) [40], which has been applied from the theory of reasoned action (TRA) [41]. The original TAM focused on predicting the actual usage behavior, including external variables as one aspect in the beginning of the model. More detailed external variables that take into account the subjective norm and prior experience of using the technology were added to the TAM2 [3].

The utility of the TAM and its extended versions for advanced technology such as robots has received some critique [42]. For example, the wide range of robotic technologies from fully teleoperated to highly autonomous devices raises questions regarding whether robots are being used by the user or if users are rather interacting with these technological entities. Some attempts at robot acceptance models have been made. For example, Heerink, Kröse, Evers, and Wielinga [43] validated the Almere model for assessing older adults' acceptance of assistive social agent technology. In addition to perceived usefulness and ease of use, the Almere model includes perceived adaptability, which is part of the instrumental aspect regarding the utility and gained benefits. However, the model has been mostly applied in eldercare research.

The unified theory of acceptance and use of technology (UTAUT) model, which has been widely used in studies regarding information technology acceptance and usage, is a combination of eight different models. In addition to the previously mentioned TAM [40] and TRA [41], the model consists of the theory of planned behavior [44], the innovation diffusion theory [45], the motivational model [46], the personal computer utilization model [47], social cognitive theory [48], and model that integrates TAM and theory of planned behavior [49]. The UTAUT model includes expected performance, effort expectancy, social influence, and facilitating conditions [50]. It has been utilized, for example, by Heerink et al. [43,51] in eldercare and, more recently, in studies by Conti et al. [18,20] on robot usage in children's education and psychology practice. In addition, the UTAUT has been used in studies measuring interaction experience with the NAO robot [52] and the acceptance and adoption of robotic surgery [53].

Attitude constructs have been discovered to play a crucial role in actual behavior also in the UTAUT model. Attitudinal beliefs and perceptions have been found to be directly associated with behavioral intention, which is in turn connected to use behavior [54]. Moreover, in the UTAUT model, behavioral intention mediates the relationship of performance expectancy, effort expectancy, social influence, and facilitating conditions to use behavior [54]. The UTAUT2 model was developed based on the UTAUT model but considering both the organizational and consumer usage contexts. The revised model includes hedonic motivation, price value, and habit [55]. Job fit is argued to be a part of performance expectancy in the UTAUT2 framework [56], and the model has been utilized, for example, in adaptation of mobile banking [57]. Thus far, research using the UTAUT2 model to examine robot acceptance remains scarce. However, in this study, we investigated the relationship between professionals' perspectives on job fit or suitability of robots and their comfortableness interacting with robots themselves. Thus, the original UTAUT model offered the most suitable theoretical framework for technology acceptance examination for the purpose of our study. Its constructs of perceived performance expectancy and behavioral intention offer an apt theoretical background for discovering the perceived suitability of robots in the service sector.

1.2 Research Overview

In this article, we report two studies that included participants from two different contexts: Finland and the United States. Both countries are highly technologically oriented, which is positively connected to robot acceptance at work [58]. The service sector's increasing trend is prominent in both countries and has been significant regarding employment for decades, especially in the United States, accounting for over 80% of the working population [59,60]. Due to the similar key characteristics of technology orientation and structure and trend of the growing service sector, we examined participants from both countries to answer our research questions. In Study 1, our main interest was to find out if there is a connection between the service sector and perceived suitability by professionals in the Finnish context. In Study 2, we aimed to replicate the finding in the context of the United States and further investigate the factors contributing to this relationship and the mediating role of perceived robot suitability for interaction attitudes of the professionals.

The results will contribute to the understanding of how the introduction of robots in new occupational fields is received as applicable among the professionals of the field.

In our studies, we considered that the service sector consists of multiple fields involving service production and customer interaction. Other sectors are classified apart from the service sector and include occupational fields such as manufacturing, agriculture, and transportation (see Appendix 1 for the full list of classifications). Considering the scarce research comparing different occupational fields on which to base hypotheses, we established research questions for our studies. Using the binary classification for the service sector, the aim of this article was to examine the following research questions:

- **H1:** How does perceived suitability of robots to one's own occupational field differ between service sector professionals and those from other fields?
- **H2:** How do the sociodemographic factors, prior experience, and attitude toward robots in general associate with perceived suitability of robots to one's field?
- **H3:** Does perceived suitability mediate the relationship between occupational sector and attitudes toward interaction with robots?

Based on technology acceptance models and previous research related to acceptance of robots, we proposed testing a short path model from the professionals' occupational field to professionals' perceptions of robot suitability to their field and further to their attitudes toward interacting with robots (see Figure 1).

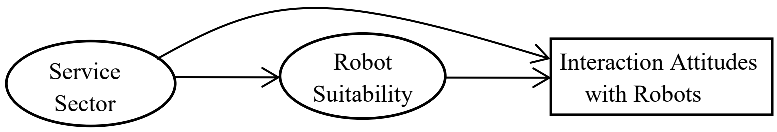

Fig. 1. Proposed path model based on research questions. Age, gender, income level, technology degree, prior interaction experience with robots, and general attitude toward robots in the model.

2 Methods and materials

2.1 Study 1

Participants. A sample from the Finnish working population was collected in March 2019. The survey participants were aged between 18 and 65 ($N = 1817$, 46.84% female, $M_{\text{age}} = 41.75$ years, $SD_{\text{age}} = 12.19$ years). We recruited the participants via Norstat's pool of volunteers, with a response rate of 28.3%. We used a stratified sampling strategy to get a sample that would represent the Finnish workforce population in terms of age and gender. Participants were informed that by completing the survey they allow the reuse of the data for further research and that they may exit the survey at any time. The academic ethics committee of Tampere region confirmed in December 2018 that the research project did not involve ethical problems.

Measures. We measured participants' attitude toward robots working in their own field by asking them to rate the following statement on a scale from 1 to 7: "My current job could be done by a robot in the future." Participants were also asked to choose their occupational field from the International Standard Industrial Classification of All Economic Activities (ISIC) list [61]. This main independent variable was created by further categorizing I–S of the ISIC list into a dummy variable, in which service sector received a value of 1 and other sectors a value of 0 (see Appendix 1). Industries were classified as part of the service sector if they provided intangible goods, in other words services, and concerned interaction with customers [62]. Our categorization of service industries was similar to those of the World Bank [63], the U.S. Census Bureau [64], and Official Statistics of Finland [65]. The same classification has also been used in other studies [66].

Sociodemographic background variables (age, gender, household's annual gross income level), were used as control variables. Age was used as a continuous variable and gender as a dummy variable. Income level was measured and used as a dummy variable by first asking about participants' monthly income in euros and then categorizing them as low- or high-income earners if they earned less than €2000 or €2000 and above, respectively. Descriptive statistics of the Study 1 variables are presented in Table 1.

Table 1. Summary of Descriptive Statistics of the Study 1 Variables ($N = 1817$).

Measure	*n*	*%*	*M*	*SD*	*Range*
Suitability of robots to one's own field	1817		2.10	1.54	1–7
Service sector	1817				0–1
1 = Service sector	1189	65.44			
0 = Other	628	34.56			
Age	1817		41.75	12.19	18–65
Gender	1817				0–1
1 = Female	851	46.84			
0 = Male	966	53.16			
Low-income earners	1817				0–1
1 = Under 2000 €	368	20.25			
0 = 2000 € and over	1449	79.75			

Statistical analyses. We analyzed the data using ordinary least squares regression analysis using sequential models. Model 1 includes only the service sector as an independent variable, and the full Model 2 includes the sociodemographic variables. In the models, we report unstandardized regression coefficients (*B*), standard error of estimate (*SE B*), standardized coefficients (β), and *p*-values for statistical significance. We did not detect multicollinearity, but because of the heteroscedasticity of residuals, we ran the models using Huber-White standard errors (i.e., robust standard errors).

2.2 Study 2

Participants. We collected data from the U.S. participants via Amazon Mechanical Turk in January and April 2019 ($N = 2072$, 50.81% female, $M_{age} = 36.98$ years, $SD_{age} = 11.43$ years); participants' age ranged from 15 to 94 years old. In line with Study 1, only the working population was considered in the final sample ($N = 1740$, 49.53% female, $M_{age} = 36.87$ years, $SD_{age} = 10.81$ years). Participants were informed that by completing the survey they allow the reuse of the data for further research and that they may exit the survey at any time. The academic ethics committee of Tampere region confirmed in December 2018 that the research project did not involve ethical problems.

Measures. To measure participants' attitudes toward robots working in their field, we asked them to rate the following statements or questions on a scale from 1 to 7. Suitability of robots to one's own field was measured with two questions: "Robots suit my occupational field well" and "My current job could be done by a robot in the future." A sum variable created from these two statements was used as the dependent variable ($\alpha = .74$). Participants were also asked to choose an occupational field that was closest to their work or study from the ISIC list. This main independent variable was a dummy variable created from the ISIC categories in the same way as in Study 1. Participants from different service fields were given a value of 1 and other participants a value of 0.

Sociodemographic background variables (age, gender, household's annual gross income level) and other independent variables relevant to the robot context (a degree in technology or engineering, prior experience interacting with robots at work, attitude toward robots) were used as control variables. Age was used as a continuous variable and gender as a dummy variable. Income level was measured and used as a dummy variable by first asking about participants' households' gross annual income and then categorizing them as low- or high-income earners if their household earned less than \$35,000 or \$35,000 and above, respectively.

We measured prior interactional experience and technological expertise of the participants to account for the critique concerning the effects of sociodemographic factors in robot acceptance research [31]. This was also critical because of the hypothetical nature of our research and rating attitudes toward robots in general versus specific robots, hence helping to consider the different images of robots people have in mind when they are scoring their attitudes. Technological expertise was measured by asking whether participants had a degree in technology or engineering or not. They also responded regarding whether they had used or interacted with robots at work before or not. Both were used as dummy variables. We also asked the participants to rate their attitude toward robots in general on a scale from 1 to 7. Descriptive statistics of the Study 2 variables are presented in Table 2.

For additional path model analysis, we measured interactional attitude by asking about participants' perceived comfortableness with interacting with robots in various ways (see Appendix 2 for the full list of questions). For example, we asked, "How comfortable would you be about shaking hands with a robot?" and "How comfortable would you be about having a conversation with a robot?" We asked participants to score their responses to 12 questions on a 7-point Likert scale from *Strongly disagree* to *Strongly agree*.

Table 2. Summary of Descriptive Statistics of the Study 2 Variables (N = 1740).

Measure	*n*	*%*	*M*	*SD*	*Range*	*n of items*	*α*
Suitability of robots to one's own field	1740		7.39	3.35	2–14	2	.75
Service sector	1740				0–1		
1 = Service sector	1326	76.21					
0 = Other	414	23.79					
Age	1737		36.87	10.81	15–94		
Gender	1718				0–1		
1 = Female	851	49.53					
0 = Male	867	50.47					
Low annual income households	1740						
1 = Under $35,000	426	24.48					
0 = $35,000 and over	1314	75.52					
Degree in technology	1740				0–1		
1 = Yes	470	27.01					
0 = No	1270	72.99					
Interaction experience with robots at work	1740				0–1		
1 = Yes	250	14.37					
0 = No	1490	85.63					
Positive attitude toward robots	1740		4.96	1.35	1–7		

Statistical analyses. We analyzed data using ordinary least squares regression analysis using sequential models. Model 1 includes only the service sector as an independent variable; in Model 2, we added the sociodemographic variables; and Model 3 is a full model of all the variables used. In the models, we report unstandardized regression coefficients (B), standard error of estimate ($SE\ B$), standardized coefficients (β), and p-values for statistical significance. Multicollinearity or heteroscedasticity of residuals was not detected. For additional analysis, we used path regression modelling and a khb package [67] for mediation examination. All the statistical analyses were conducted with Stata 12 and Stata 16 programs.

3 Results

3.1 Study 1

We present the results with two linear regression models in Table 3. Service sector professionals perceived robots as less suitable in their field (β = −.08, p = .001), as shown in Model 1. The negative connection remained after adding age, gender, and household's annual gross income as controls in Model 2 (β = −.07, p = .002). In Model 2, with sociodemographic control variables, older age predicted lower perceived suitability (β = −.18, p < .001). Gender was found to be unrelated to perceived suitability (β = −.01, p = .752). Higher income was found to be negatively connected to perceived suitability (β = −.08, p < .001). The final model was statistically significant (p < .001) and explained 6% of the variance.

Table 3. Suitability of Robots to One's Own Occupational Field in Study 1 (N = 1817).

	Model 1 ROBUST			Model 2 ROBUST		
Measure	*B*	*SE B*	β	*B*	*SE B*	β
Service sector	−.26	.08	−.08**	−.24	.08	−.07**
Age				−.02	.00	−.18***
Gender (female)				−.02	.07	−.01
Low-income earners				.48	.10	.13***
Model R^2		.01			.06	
Model F		11.53			26.51	
Model p		***			***	

Note. Dependent variable: Suitability of robots to one's own occupational field sum variable. *p < .05. **p < .01. ***p < .001.

3.2 Study 2

We present the results with three linear regression models in Table 4. As in Study 1, service sector professionals perceived robots as less suitable in their field (β = −.06, p = .008), as shown in Model 1. The negative connection remained after adding age, gender, and household's annual gross income as controls in Model 2 (β = −.06, p = .013). The relationship of the service sector and perceived suitability of robots in their own field was still statistically significant after adding strong predictor variables in Model 3 (β = −.06, p = .011).

Higher income was not found to be connected to perceived suitability, based on Model 2 (β = −.01, p = .646) and Model 3 (β = −.03, p = .150). Older age predicted lower perceived suitability in both Model 2 (β = −.20, p < .001) and Model 3 (β = −.17, p < .001). A negative connection between the female gender and lower perceived suitability was found in Model 2 (β = −.07, p = .002), but it disappeared after adding technology degree, prior interactional experience with robots at work, and attitude toward robots in Model 3 (β = –.00, p = .910). A degree in technology was the strongest predictor in Model 3, predicting higher perceived suitability (β = .23, p < .001). Prior interactional or user experience with robots at work predicted higher perceived suitability (β = .12, p < .001). Positive attitude toward robots was also connected to high perceived suitability (β = .16, p < .001). The final model was statistically significant (p < .001) and explained 17% of the variance in perceived suitability.

Table 4. Suitability of Robots to One's Own Occupational Field in Study 2 (N = 1740).

	Model 1 (N = 1740) ROBUST			Model 2 (N = 1715) ROBUST			Model 3 (N = 1715) ROBUST		
Measure	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Service sector	–.50	.19	–.06**	–.46	.18	–.06*	–.44	.17	–.06*
Age				–.06	.01	–.20***	–.05	.01	–.17***
Gender (female)				–.49	.16	–.07**	–.02	.15	–.00
Low annual income households				.09	.19	.01	.25	.18	.03
Degree in technology							1.74	.18	.23***
Interaction experience with robots at work							1.12	.21	.12***
Positive attitude toward robots							.39	.06	.16***
Model R^2		.01			.05			.17	
Model F		10.99			24.28			57.34	
Model p		***			***			***	

Note. Dependent variable: Suitability of robots to one's own occupational field sum variable.
$*p < .05$. $**p < .01$. $***p < .001$.

Results of the additional analyses are shown in a path model in Figure 2. According to the path model, being in the service sector predicts lower perceived robot suitability (B = –.44, SE = .17, β = –.06, p = .012) and perceived suitability in turn predicts positive interaction attitudes (B = .60, SE = .10, β = .12, p < .001). Working in the service sector does not directly decrease the probability of positive interaction attitudes before or after controlling for perceived robot suitability to one's field. However, working in the service sector, or more accurately a standard-deviation increase in the service sector variable, leads to lower perceived robot suitability to one's own field, which is then translated into a lower probability of positive interaction attitudes of 26.44 percentage points, on average. The difference between the full and reduced model, hence the mediating effect of robot suitability, is statistically significant (z = –.26, p = .021), and the confounding percentage for the service sector variable is 36.79%.

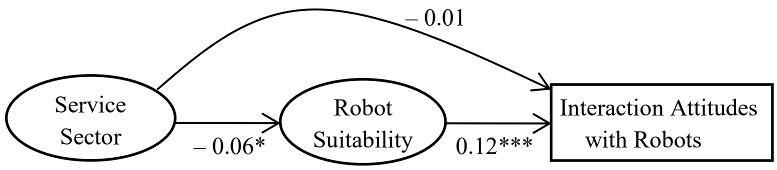

Fig. 2. The estimated path model in Sample 2 ($N = 1740$). Age, gender, income level, technology degree, prior interaction experience with robots, and general attitude toward robots in the model.

4 Discussion

In this work, we investigated whether service sector professionals consider robots as applicable to their own field as people from other sectors. We collected survey data from two countries, Finland and the United States. Based on both cultural backgrounds, service sector professionals perceived robots as less suitable to their own occupational field than did professionals from other fields. Young participants were more likely to consider robots suitable to their own field in both samples. Low-income was associated with perceived robot suitability only in Finnish working population, and no difference between genders was found in either cultural background. In addition, examination of U.S. respondents revealed that technology education, prior experience interacting with robots at work, and general positive attitude toward robots were positively connected with perceived suitability of robots to one's own occupational field. The path model analysis supports our proposed model in which service sector is negatively connected to attitude toward interacting with robots via perceived robot suitability (Figure 2).

Our results indicate that robots entering the service sector evokes more negativity concerning suitability in associated professionals than in those of other occupational fields, which is in line with previous research results concerning lower perceived suitability of robots to social or artistic fields of work [12,13]. Hesitant reception of robots in the service sector may derive from shorter history in utilizing robots in these fields compared to industries such as manufacturing. Furthermore, a lack of knowledge about the technological potential of advanced service robots and prior experience with robots in the work context contribute to perceived suitability of robots to one's occupational field.

In agreement with this, our analyses show that the relationship between occupational sector and perceived suitability is affected by age, technology expertise, prior interactional experience with robots at work, and attitudes toward robots. Older participants were less likely to consider robots suitable even after controlling for technological expertise and prior experience with robots at work, which somewhat contradicted previous research concerning domestic and eldercare robots, although the direction of the relationship remained the same [31,32]. However, the effect of gender disappeared after controlling for technological expertise and prior robot experience, confirming the suspicions of previous researchers about the controlling effect of prior technological experience at least in the case of gender [32]. The association of income was not confirmed due to the mixed results regarding low-income respondents' positive response on robot suitability. Future researchers should investigate the income factor further, especially because research concerning sociodemographic factors behind acceptance of robots has produced mixed results in the literature also before. One reason for mixed result could also be cultural variation that has been noted previously [68].

Finally, the additional analysis of interactional attitudes highlights how the negative perceptions of the service sector professionals could impact their intention and actual use of and interaction with robots. According to the TAM, Almere model, and UTAUT model, attitudinal beliefs of perceived usefulness, adaptability, job fit, and performance expectancy play a key role in acceptance to use or interact with robots. In UTAUT model, for example, expectations also predict behavioral intention and actual behavior [49,52]. Therefore, as our findings indicate, negative attitudes toward robot suitability can decrease both the intention and the actual use of robots in the service sector.

It has also been noted that the social acceptance of robot workers may be dependent on the characteristics of the robot, for example, appearance, level of autonomy, or task compatibleness. In addition to the comprehensive investigations of the factor of robot appearance [69,70,71], future studies should continue to investigate the impact of robot autonomy level on social acceptance and the sense of autonomy of the interacting human [72]. Future research should also investigate if online service context yields different results, as some evidence indicates trusting behavior when humans are replaced by robots and artificial intelligence in gamified online environment [73].

Our results contribute to the understanding of how the introduction of robots in new occupational fields is perceived by service sector professionals compared to professionals from other sectors. When developing new generations of service robots and planning to introduce them into new fields of work, it should be noted that the resistance might challenge the deployment of robots in the service field in particular. Although the service sector consists of multiple different occupational fields, these fields share similarities in customer interaction, uncertainty about the abilities of the new advanced robots, and possible fear of being replaced by robots. Therefore, sustainable policy and technology development should consider workers' and professionals' acceptance of deploying robots in their own field of work. Providing early technological education and interactional experience with robots and enhancing knowledge about the advancement and potential of technology are essential for the perceived suitability and acceptance of robots in the service sector.

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Disclosure statement
The authors report no conflict of interest.

Appendix 1
The following is the International Standard Industrial Classification of All Economic Activities (ISIC) list. Industries included in the service sector are in *italics*.

A. Agriculture, forestry and fishing
B. Mining and quarrying
C. Manufacturing
D. Electricity, gas, steam and air conditioning supply
E. Water supply; sewerage, waste management and remediation activities
F. Construction
G. Wholesale and retail trade; repair of motor vehicles and motorcycles
H. Transportation and storage
I. Accommodation and food service activities
J. Information and communication
K. Financial and insurance activities
L. Real estate activities
M. Professional, scientific and technical activities
N. Administrative and support service activities
O. Public administration and defense; compulsory social security
P. Education
Q. Human health and social work activities
R. Arts, entertainment and recreation
S. Other service activities
T. Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U. Activities of extraterritorial organizations and bodies

Appendix 2
The following questions were used in path analysis for measuring participants' perceived comfortableness with interacting with robots.

How comfortable would you be about
… using a robot as equipment at work?
… having a robot as your co-worker?
… shaking hands with a robot?
… hugging a robot?
… robot giving you a pat on the back?
… giving a robot a pat on the back?
… robot's surface being hard when touching it?
… robot's surface being soft when touching it?
… having a conversation with a robot?
… asking robot a question?
… responding to robot's question?
… robot following your movements with its gaze?

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