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Health Care Workers' Attitudes Towards Social Robots. Some Empirical Evidence*

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Abstract

The application of social robots is spreading to many different areas of daily life. They are being used for tasks such as health monitoring, caregiving assistance and educational activities. The use of robots has sociological implications due to the fact that some nations are facing challenges associated with ageing populations and a shortage of workers in certain sectors, including healthcare. Social robots are being considered as one way of addressing these challenges. Understanding the extent to which workers accept the use of social robots is important for social research. The aim of this paper was to identify the sociodemographic and work-related factors that influence health care workers' attitudes towards social robots. A non-representative sample of 302 health care workers was analysed. The General Attitudes Towards Robots Scale (GAToRS) was used to measure attitudes towards social robots. The results show that although the topic of robotics has become familiar to health care workers and they generally express positive views about them, most have not had much personal experience of their use. Additionally, health care workers expressed a high level of interest in the scientific discoveries and technological developments of social robots, and this could contribute to developing acceptance among these professionals regarding their use.

Keywords: social robots, social assistance, health care workers.

* Although the work is the expression of all authors, the sections are attributed as following: paragraph 2 was written by Elena Bertuzzi, Naomi Bonito and Francesca Trivellato, under the supervision of Marco Carradore. The section 6 (Conclusions) was written by all authors. All the other sections are to be attributed to Marco Carradore.

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1. Introduction

The use of social robots is rapidly increasing in many different sectors, thus expanding the application of robotics from mainly industrial settings, where they have long been used, towards public and private settings (Čaić et al., 2019). Evidence of public use of social robots can be seen in many different areas, such as healthcare, where social robots are used, for example, as assistive devices (Green et al., 2016), hospital settings, where social robots are adopted, for instance, for health monitoring and caregiving assistance (González-González et al., 2021), and education, where some applications include tutoring and the facilitation of peer learning (Belpaeme et al., 2018).

The use of social robots is also spreading geographically. In some areas of the globe, such as Japan, there is a consolidated culture of robots (Šabanović, 2014; Samani et al., 2013). In other regions of the world, such as in European nations, the diffusion of social robots is under current expansion. In Italy, for example, experience of the use of social robots, as well as artificial intelligence, is rapidly increasing year after year, as demonstrated by the scientific literature (Bevilacqua et al., 2023; Cingolani et al., 2023; Veronesi et al., 2023) and news reports on social robots published in newspapers (Righetti and Carradore, 2019).

Social robots have been defined in different ways. Dautenhahn and Billard (1999), for example, propose to define the social robot as 'embodied agents that are part of a heterogeneous group: a society of robots or humans. They are able to recognize each other and engage in social interactions, they possess histories (perceive and interpret the world in terms of their own experience), and they explicitly communicate with and learn from each other' (in Fong et al., 2003, p. 144). Bartneck and Forlizzi (2004), on the other hand, defined a social robot as an 'autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact' (in Lopes et al., 2023, p. 894). Breazeal et al. (2016, p. 1936) considered that 'social robots are designed to interact with people in human-centric terms and to operate in human environments alongside people. Many social robots are humanoid or animal-like in form, although this does not have to be the case. A unifying characteristic is that social robots engage people in an interpersonal manner, communicating and coordinating their behavior with humans through verbal, nonverbal, or affective modalities.' Despite the different definitions, we can identify some common aspects in them, namely that a social robot is a physically embodied, autonomous agent that interacts and communicates with humans.

Since the use of social robots is also spreading across different contexts in Italy and is likely to continue to grow, social research should invest more in analysing this phenomenon to support the private companies involved in their development as well as the public sector interested in their application.

The aim of this study was to analyse health care workers' attitudes towards social robots. Considering the increasing use of social robots in the health care sector, gathering information on how workers involved in this area feel towards their robotic 'colleagues' operating with artificial intelligence is of great importance.

The paper is divided into the following sections. Section 2 presents some examples of social robots used in the health care area and underlines the implications of the use of robots. The instruments available for measuring attitudes towards social robots are presented and the research question explicated. Section 3 presents the data and the analysis carried out, and section 4 presents the results. The final section draws some conclusions.

2. The spread of the social robots

Advancements in robotics and artificial intelligence have supported the creation of different kinds of robots capable of interacting with humans and doing different tasks. Kyrarini et al. (2021) analysed some of the nonsurgical robots used to support healthcare workers such as caregivers and therapists, clustering them into five categories which they defined as assistive, care, hospital, rehabilitation, and walking-assistant robots.

In the group of assistive robots, the researchers included robots such as the Friend system, Jaco 2 robotic and the Baxter humanoid robot. The first is an intelligent wheelchair-mounted manipulator which is now in its fourth generation. It is able to support individuals with quadriplegia in real-world environments. This wheelchair platform is equipped with a robotic arm with a two-finger gripper and a hand camera, a chin joystick and head control interface, a stereo-camera, and a laser scanner. The Jaco 2 robotic is a robot used mainly in research for assisting with drinking and eating tasks as well as with manipulation tasks. This system is also equipped with an arm with a two-finger gripper, sensors, and a camera to identify the food on a plate. It has an online learning framework developed for successful bite acquisition. The Baxter humanoid robot is an example of an assistive robot developed to assist in dressing its users. In experimental tests of users with simulated upper-body impairments, the robot was demonstrated to be able to provide personalized dressing assistance in putting on a sleeveless jacket (Kyrarini et al., 2021).

In the group of care robots, the researchers included the Pepper robot, which can be used, for example, as a companion for elderly people (Yang et al., 2017). Its appearance is semi-humanoid. It has wheels and a camera on its head, and like the other robots it has a microphone, a tactile sensor for perceiving the world, and two speakers where the ears would be on a human, while on its torso there is a touch display. Another care robot is PHAROS, which is designed to help the elderly by suggesting and monitoring their daily physical activities at home (Costa et al., 2018). The advantage of this robot is that it records subjects while exercising and produces data that is then fed into a system that recognizes the type of exercise being performed and generates a sequence of exercises encapsulated in each user's daily schedule. Another important assistive characteristic of the PHAROS robot is that it provides verbal commentary as well as visual demonstrations geared towards assisting the user to comprehend the proposed exercise. Lio (Mišeikis et al., 2020) is another care robot and it is being subject to evaluations in different nursing and retirement facilities in Germany and Switzerland, as well as for the provision of support at home (Kyrarini et al., 2021). Its body is equipped with different sensors and a support for holding bottles or cups. It has a screen, speakers, and omnidirectional microphones on its base. Like other robots, it can move autonomously, and its functionality is hybrid, with some tasks being carried out exclusively autonomously and other tasks being controlled by a user.

Three examples of robots being applied in hospital settings are Moxi, ROBEAR and the Adaptive Robotic Nursing Assistant (ARNA). Moxi was developed to assist nurses in hospitals and clinics. It can retrieve and brings supplies to hospital rooms and nursing stations, delivers samples to laboratories, and removes bags of soiled linen. Moxi is able to manipulate objects known in advance and navigate in a fully autonomous and safe manner, avoiding both static and dynamic obstacles. The main duties of ROBEAR are to lift the patient from a bed into a wheelchair and help a patient into a standing position. Finally, ARNA 'is a multipurpose robot that helps nurses with day-to-day tasks, such as walking patients, fetching objects, and monitoring patients' health' (Kyrarini et al., 2021, p. 9).

In relation to the final two robot categories, as set out by Kyrarini et al. (2021), those intended for rehabilitations purposes include Lower Limb Rehabilitation (LLR), Lokomat, and Balance Assessment Robot for Treadmill walking (BART); while those developed as walking assistant 'technologies' include Walking-Frame based Walking Assistants (WWA), the Walbot robot, and the assistive robotic system iWalk. LLR provides help for patients with lower limb disorders, improving patients' physical status by enhancing muscle vitality. This device combines mechanical power with artificial intelligence, and it provides a key solution to the nursing shortage problem brought on by aging populations (Zhou et al., 2021). The Lokomat is an example of a robot that supports patients achieve an upright position and it helps them move their legs according to natural motor patterns (Mikolajczyk et al., 2018). BART is a technological robot that evaluates a patient's balance skills while they are walking (Zadravec et al., 2020). The WWA is a walker robot, mainly used in indoor scenarios, providing more stability and support to the walker. Usually, these technologies incorporate additional assistive features like rehabilitation exercise monitoring and sit-to-stand assistance. Walbot is another intelligent robot with shared-control of walking-assistant. The robot i-Walk is a rollator assistive device designed to support a wide range of motor and cognitive assistance functionalities (Kyrarini et al., 2021).

The development of robotic technology has permitted robots to operate in increasingly complex contexts, involving multiple stakeholders, and to include more human features and the ability to recognize and respond to human facial expressions (Rawal and Stock-Homburg, 2022).

The spread of the use of robots in many areas of daily life also has sociological implications since most nations have to face challenges associated with ageing populations (Cristea et al., 2020) as well as a shortage of workers in the related sectors such as healthcare (Michel and Ecarnot, 2020). Thus, social robots can be considered as providing a much-needed support within various social environments (Čaić et al., 2019).

For these reasons, understanding the level of people's acceptance of social robots is an important research topic. Based on the previous considerations, the current study focuses on which aspects impact attitudes towards social robots in a specific area, namely the healthcare sector, where social robots are already operative in many areas. Thus, the research question of the present work was the following: what are the sociodemographic and work factors that influence health care workers' attitudes towards social robots?

Some of the findings achieved in previous studies show, for example, that older adults appreciate interactions with robotics, but they do not want robots to replace caregivers (Carros et al., 2020). Chen et al. (2020) demonstrated, through their research on long-term care, 'that positive attitudes might facilitate health personnel acceptance and adoption of social robots for older people' (Chen et al., 2020, p. 1145). Kang et al. (2023) underlined that it should be beneficial to introduce care robots and socially assistive technologies as assistive tools for older adults since the caregivers are burdened by their workload. Thus, educating healthcare personnel about care robots and social assistance technologies in general is of great importance. This was also highlighted by Turja et al. (2018), who found that healthcare professionals have less experience of robots than the general population as well as negative attitudes towards robots. However, the medical field has welcomed robotic assistance for certain tasks, such as the transportation of heavy goods and logistics. In addition, the authors noticed that previous experience of robots consistently correlated with greater robot acceptance. The potential of the use of social robots is also mentioned also by Klebbe et al. (2023), who also state, however, that the use of assistance of robots should be accompanied by high levels of professional supervision to guarantee patient safety and to develop 'work awareness' in the caregivers, which regards the caregiver's responsibility and situational awareness for the care recipient throughout the entire care process. On the other hand, there is also the notion that caregivers may fear their jobs being replaced by robots, as has occurred in other industries (Kyrarini et al., 2021).

Thus, the debate about the adoption of social robots is very much open and requires more analysis, including the taking into consideration of how attitudes are measured. Indeed, various scales are present in the literature for measuring attitudes towards social robots, each of which focuses on distinctive aspects. For instance, the Negative attitudes towards robot scale (NARS) is composed of 14 items, and focuses on negative attitudes only (Nomura et al., 2006); the Ethical acceptability scale (EAS) constitutes twelve items and was 'first developed to assess ethical issues in the use of robot-enhanced therapy with children with autism' (Mlakar et al., 2022, p. 3); the Technology-specific expectation scale (TSES), composed of ten items (Alves-Oliveira et al., 2015), was proposed to provide a measure of baseline expectations 'specific to intended interactions with a particular robot, which may be based on unrealistic preconceived ideas from exposure to science-fiction culture' (Krägeloh et al., 2019, p. 6); and the Frankenstein syndrome questionnaire (FSQ), composed of 30 items, which is only applicable to humanoid robots (Syrdal et al., 2013). The first two scales are divided into three subscales, while the TSES is divided into two and the FQS into four sub-dimensions. Other scales adopted are the Robotic social attributes scale (RoSAS), composed of 18 items divided into three sub-scales (Carpinella et al., 2017),[1] and the recent General Attitudes Towards Robots Scale (GAToRS), composed of twenty items divided into four sub-scales. The latter scale was the instrument used in the present study to

[1] The NARS subdimensions are the 'negative attitudes toward situations of interaction with robots,' (six items) the 'negative attitudes toward the social influence of robots,' (five items) and the 'negative attitudes toward emotions in interaction with robots' (three items); the first subscale of the EAS is called 'Ethical Acceptability for Use' (five items), the second 'Ethical Acceptability of Human-like Interaction' (four items), and the third 'Ethical Acceptability of Non-Human Appearance' (three items). TSES is composed of the 'Capabilities dimension' and 'Fictional view' factors (both with five items). The four FQS subdimensions are 'General anxiety toward humanoid robots' (13 items), 'Apprehension toward social risks of humanoid robots' (5 items), 'Trustworthiness for developers of humanoid robots' (4 items), and 'Expectation for humanoid robots in daily life' (5 items), the sum of the items is not 30, since three items were excluded due to the results of the analysis. The RoSAS subdimensions are 'Competence,' (six items), 'Warmth,' (six items) and 'Discomfort' (six items).

assess attitudes towards social robots. The advantage of this scale is that it focuses on four different aspects of social robots, namely a) comfort and enjoyment, b) unease and anxiety, c) reasonable hopes, and d) reasonable worries (Koverola et al., 2022).

3. Data and analyses

The data used in this analysis form part of a larger research project, one of the main aims of which is to validate the GAToRS scale in the Italian language.[2] The data were collected through a survey administered to hospitals and rest homes in the northeast of Italy, which gave informed consent for their participation in the research. A questionnaire was specially created using the GAToRS items plus other sociodemographic questions. The questions are clustered into four main areas: one addressing socio-demographics and the employment aspects of the interviewees; a second related to interest in and familiarity with social robots (this section has four items: i) robotics is a familiar topic to me; ii) generally speaking, I have a positive view of robots; iii) I have personal experience of using robots, and iv) I am interested in scientific discoveries and technological developments); the third section presents the GAToRS scale; and the fourth section asks an open question on the topic of social robots. Since the data were collected in hospitals and rest homes, to ensure greater anonymity of the participants the variables related to the respondent age and the number of years of work were formulated in the categorical format. The other data gathered using the categorial format addressed: gender, education level, area of work and work sector. The questionnaire takes approximately fifteen minutes to answer. The survey was carried out from 13th October 2022 to 10th January 2023 through an online survey conducted using the Lime Survey platform. The Limes Survey link was sent to the employees in the organizations participating in the project by their managers, who asked them to fill the questionnaire in.

A total of 306 health care workers completed the questionnaire. Four cases were excluded from the analysis. Two were not directly involved in health care but in administrative and educational duties, and the other two were excluded because they did not specify their area of work. The non-probability sample is thus composed of 302 cases.

[2] The project was carried out as part of the master's degree in 'Infermieristica di Famiglia e di Comunità e Assistenza Integrata per la Salute Collettiva' (Master I livello), University of Parma, Italy.

Since the main aim of this research was to identify what dimensions impact health care workers' attitudes towards social robots, a regression approach was applied. First, the frequency of each single variable was analysed, then the relations between each pair of variables related to the robot issue were considered. The third step was to apply exploratory factor analysis, EFA (Watkins, 2020), to identify the four latent dimensions of the GAToRS scale, as in the literature (Koverola et al., 2022). The variables that compose the four factors that emerged from the EFA were thus used to compute, applying the additive method, the dependent variable used in the regression models.[3] We computed two regression models for each factor, one using the sociodemographic and work condition variables only, whereas the second model also included the variable 'familiarity of and experience with robots', as well as the variable that measured interest in scientific discoveries and technological developments.

4. Results

This section presents the distribution of each variable related to the sociodemographic features, the work condition aspect and the variables related to social robots. The eight regression models are then presented.

4.1 Sociodemographic characteristics of the sample

The sociodemographic characteristics of the survey participants are presented in table 1.

The sample is mainly composed of women, which make up approximately 80% of the sample. The most common age range was 46-55 years (30.46%), the next was 26-35 years old (28.48%), followed by 36-45 years old (23.84%). Only 13% fell into the oldest category, over 55 years, while approx. 4% were aged less than 26 years old.

With regard to education level, 43.05% reported having a university degree, and 34.11% had secondary school level education. Around 23% of the sample had a post university degree.

[3] The analyses were carried out with R Studio (2023.06.0+421), packages FactoMineR, factoextra and lm.

Table 1. Sociodemographic characteristics of the survey participants.

Sociodemographic characteristics	%	N
- Gender		
Male	20.53	62
Female	79.47	240
Total	100.00	302
- Age		
Less than 26 years	4.30	13
26 to 35 years	28.48	86
36 to 45 years	23.84	72
46 to 55 years	30.46	92
Over 55 years	12.91	39
Total	100.00	302
- Education		
Secondary school	34.11	103
University degree	43.05	130
Post University degree	22.85	69
Total	100.00	302

4.2 Health care worker characteristics

The information describing the work carried out by the survey participants were: main area of employment, the sector of work, and the number of years spent performing the same work activities.

Table 2. Work characteristics of the participants at the survey.

Work characteristics	%	N
- Area of employment		
Social health care	21.85	66
Healthcare	78.15	236
Total	100.00	302
- Years of working in the actual role		
Less than 11 years	38.74	117
From 11 to 20 years	25.50	77
From 21 to 30 years	20.86	63
More than 30 years	14.90	45
Total	100.00	302
- Sector of work		
Hospital	60.93	184
Local healthcare unit	12.58	38
Care home	22.52	68
Other	3.97	12
Total	100.00	302

Table 2 summarises the statistics related to this variable: 78% of the participants reported to work in healthcare, while approximately 22% were occupied in social health care. Sixty-one percent worked in hospitals, whereas around 13% worked in a local health care unit and this refers to that they deliver healthcare services to a specific territorial area. Twenty-two percent declared to work in the care home sector, and approximately 4% worked in other sectors. Regarding the number of years working in their present job role, approximately 39 % less than 11 years of experience; while 25% reported 11 to 20 years. Twenty percent of respondents had worked for 21 to 30 years in their jobs, while around 15% had accumulated more than 30 years of work experience.

The sample is mainly composed of female workers employed by hospitals with at least 20 years of work experience.

4.3 The social robot dimensions

The questions concerning social robots in the questionnaire are divided into two groups: four questions considered general questions which help to identify the respondents' confidence with and familiarity of social robots and technology in general, and twenty questions relate to the GAToRS scale (Koverola et al., 2022). All of these variables were rated using a 7-point Likert scale, where 1 means 'strongly disagree', and 7 means 'strongly agree'.

Table 3. Attitudes towards social robots.

Attitudes	Mean	SD	Median	Min	Max	N
Robotics is a familiar topic to me	3.18	1.73	3.00	1	7	302
Generally speaking, I have a positive view of robots	3.92	1.60	4.00	1	7	302
I have personal experience of using robots	2.08	1.66	1.00	1	7	302
I am interested in scientific discoveries and technological developments	5.41	1.70	6.00	1	7	302

The first group of variables is described in table 3. The mean score for the first variable, which measures whether robotics is a familiar topic to participants, is 3.18 (standard deviation 1.73). The mean score for the variable 'Generally speaking, I have a positive view of robots' is 3.92 (standard deviation 1.60). Health care workers appear to have little experience of using robots, because the mean score for this variable is just 2.08 (standard deviation 1.66). The mean score for the variable that measures interest in scientific discoveries and technological developments in robotics was the highest at 5.41 (standard deviation 1.70). Thus, overall, it appears that the health care workers interviewed were interested in technology and its use, but they did not have much direct experience of working with social robots.

The analysis of the EFA (rotation 'promax') confirms that the twenty items can be split into four main factors, as also reported by Koverola et al. (2022), the eigenvalues for which are 6.12, 3.19, 1.85, and 1.43, respectively; the eigenvalue value for a 5th factor was less than 1. The total amount of variance described by the four factors is 52%. The five variables loaded in each latent dimension were thus added together and divided by their number. The results were used to represent the four dimensions of the GAToRS scale. Table 4 reports some statistics concerning these latent factors.

Table 4. The four dimensions of the GAToRS scale.

Dimensions	Mean	SD	Median	Min	Max	N	Cronbach's alpha
Personal level positive (P+): comfort and enjoyment around robots	3.50	1.39	3.40	1	7	302	0.86
Personal level negative (P−): unease and anxiety around robots	3.01	1.42	2.80	1	7	302	0.84
Societal level positive (S+): rational hopes about robots in general	4.72	1.44	4.80	1	7	302	0.87
Societal level negative (S−): rational worries about robots in general	4.98	1.23	5.20	1	7	302	0.74

The mean value of the personal positive level (comfort and enjoyment around robots) is equal to 3.5 (standard deviation 1.39), and the mean value of the personal negative dimension was roughly the same (mean 3.1, standard deviation 1.42). The mean value for the two dimensions which represent the social level of the scale are slightly higher: 4.72 for the societal positive level (standard deviation 1.44) and 4.98 for the societal negative level (standard deviation 1.23).

Table 5. Correlation of variables related to social robots and the four dimensions GAToRS scale.

	1	2	3	4	5	6	7	8
Robotics is a familiar topic to me	1.00							
Generally speaking, I have a positive view of robots	0.58	1.00						
I have personal experience of using robots	0.59	0.44	1.00					
I am interested in scientific discoveries and technological developments	0.32	0.47	0.21	1.00				
Personal level positive (P+): comfort and enjoyment around robots	0.42	0.73	0.30	0.39	1.00			
Personal level negative (P−): unease and anxiety around robots	-0.04	-0.31	-0.09	-0.16	-0.30	1.00		
Societal level positive (S+): rational hopes about robots in general	0.27	0.54	0.22	0.39	0.51	-0.14	1.00	
Societal level negative (S−): rational worries about robots in general	-0.11	-0.30	-0.04	-0.01	-0.31	0.36	-0.10	1.00

Cronbach's alpha values, a measure of internal consistency, were calculated for each dimension and are indicated in the last column of table 4. The societal negative level is lowest compared with the other three dimensions; however, a value ≥ 0.7 can be considered acceptable. The values of Cronbach's alpha for the other three dimensions were ≥ 0.8, which is considered good (Taber, 2018). Thus, considering the values of the Cronbach's alpha, we can affirm that the measures are reliable.

Since the variables related to social robot issues are continuous, it is useful to consider the relationship between them and the dimensions of the GAToRS scale. These results are reported in table 5. The correlation between the variable 'Generally speaking, I have a positive view of robots' and the variable 'Personal level positive (P+): comfort and enjoyment around robots' is equal to 0.73, whereas the correlation between the first and the variable 'Societal level positive (S+): rational hopes about robots in general' is 0.54. None of the other variables showed a high level of correlation.

Considering the high level of correlation between the variable 'Generally speaking, I have a positive view of robots' and the two dimensions of the GAToRS scale, it was considered appropriate to exclude this variable from the set of independent variables.

4.4 Effects on the general attitude towards social robots

The results of the regression models are described in tables 6 and 7. The first reports data related to personal attitudes towards social robots (positive and negative), whereas the second concerns the social features of these attitude. Only statistically significant values are reported. Due to the presence of a statistically significant relationship between the age of interviewees and the number of years of work, only the years of work was considered as an independent variable in the regression models, avoiding the problem of multicollinearity.[4]

Considering the first model, which uses the personal level positive attitude as the dependent variable, we can see that only those employed in the care home sector, and not those working in hospitals, have a significant impact on the variable 'feel comfort and enjoyment around robots'. However, the R-squared (and the Adjusted R-squared) of this model's values are irrelevant. When the independent variables related to experience, familiarity with robots and interest in technologies are added to this model, it changes, increasing the proportion

[4] Regression models were also computed using respondent age as the independent variable (excluding the years of work), and the models obtained the same results.

of the variance explained by the model to 24%. The variables that are statistically significant with a positive impact on the personal positive component of the GAToRS scale are 'being familiar with robots' and 'being interested in scientific discoveries and technological developments'. These two variables increase the dependent variable by 0.23 and 0.22 points, respectively, while the other independent predictors are constant. None of the socio-demographic or employment features have any impact.

Table 6. Regression model with dependent variables the personal positive and negative levels.

	Sc_PPA Personal level positive (P+): comfort and enjoyment around robots						**Sc_PNA Personal level negative (P−): unease and anxiety around robots**					
	B	**SE (ß)**	**ß**	***B***	**SE (ß)**	**ß**	***B***	**SE (ß)**	**ß**	***B***	**SE (ß)**	**ß**
Gender												
Male												
Education												
University degree												
Post University degree												
Employment area												
Social health care							0.53*	0.23	0.15	0.55*	0.23	0.16
Working years												
11-20 years												
21-30 years							0.47*	0.23	0.13	0.47*	0.22	0.13
More 30 years												
Working sector												
Care home	0.44*	0.21	0.13									
Local unit												
Other												
Familiar				0.23***	0.05	0.29						
Experience												
Interest				0.22***	0.04	0.27				-0.10*	0.05	-0.13
Intercept	3.29***	0.24	0.24	1.39***	0.30		2.82***	0.24		3.41	0.34	
N		302			302			302			302	
R-squared		0.04			0.28			0.07			0.09	
Adj. R-squared		0.01			0.24			0.04			0.05	
AIB		1066.77			987.65			1071.18			1069.66	
BIC		1111.29			1043.30			1115.71			1125.31	

Signif. codes: 0 '***', 0.001 '**', 0.01 '*', ' ' 0.05.
Reference categories: Gender: Female; Education: Secondary school; Employment area: Healthcare; Working years: Less than 10 years; Working sector: Hospital.

Focusing on the models that analyse which variables impact personal unease and anxiety around robots, we can see that being employed in social health care, compared to being in healthcare, increases the effect by 0.15 points on the dependent variable, while the other independent variables remain constant. The variable which measures the years of work also has a positive impact on the dependent variables. Being employed from 21 to 30 years vs less than 10 years is associated with a greater level of personal unease and anxiety around social robots (0.13 points higher). The values of R-squared and Adjusted R-squared are low and approximately the same for the two different models.

Table 7. Regression model with dependent variables the societal positive and negative levels.

	Sc_SPA Societal level positive (S+): rational hopes about robots in general						**Sc_SNA Societal level negative (S−): rational worries about robots in general**					
	B	**SE (ß)**	**ß**	***B***	**SE (ß)**	**ß**	***B***	**SE (ß)**	**ß**	***B***	**SE (ß)**	**ß**
Gender												
Male												
Education												
University degree												
Post University degree	0.53*	0.25	0.15									
Employment area												
Social health care												
Working years							-0.46*	0.18	-0.16	-0.45*	0.18	-0.16
11-20 years												
21-30 years	0.52*	0.23	0.14	0.49*	0.21	0.13						
More 30 years	0.55*	0.26	0.13	0.51*	0.24	0.12	-0.52*	0.23	-0.15	-0.48*	0.23	-0.13
Working sector	0.45*	0.22	0.13									
Care home												
Local unit				0.59*	0.24	0.13						
Other												
Familiar												
Experience												
Interest				0.27***	0.04	0.32						
Intercept	3.96***	0.24		2.18	0.32		5.20***	0.21		5.31***	0.30	
N		302			302			302			302	
R-squared		0.06			0.22			0.04			0.05	
Adj. R-squared		0.02			0.18			0.01			0.01	
AIB		1084.17			1032.95			993.63			996.38	
BIC		1128.70			1088.61			1038.16			1052.04	

Signif. codes: 0 '***', 0.001 '**', 0.01 '*', ' ' 0.05.

Reference categories: Gender: Female; Education: Secondary school; Employment area: Healthcare; Working years: Less than 10 years; Working sector: Hospital.

With regard to the positive societal dimensions of the scale, the variables with a positive impact on the dependent factor are education level, years of work, and sector of work. The mean score for rational hopes about robots was 0.15 points higher for respondents with a postgraduate university than for those with a secondary school education only, while the other independent variables were constant. Having worked in the same job for 21 to 30 years was associated with an outcome variable 0.14 points higher compared with having worked in the same role for less than 10 years. All other predictors were constant. Thirty years of work experience or more had approximately the same effect on the dependent factor, since the standardized beta was equal to 0.13. The score for rational hopes about social robots was 0.13 points higher for the survey participants employed in care home compared with those working in the hospital setting. All other predictors were constant.

Adding the variable related to robot issues to the previous model, the effects of the predictors change and the proportion of variance in the dependent factor that can be explained by the independent variable increases to 18%.

The last two models address rational worries about robots as the outcome variable. In relation to the sociodemographic and work condition predictors only, we find that the score for rational worries about robots is 0.16 points lower in those with 11 to 20 years work experience than in those working in the same job for 10 years or less. The effect of working for more than 30 years was a reduction in the dependent variable by 0.15 points compared with those who had worked for 10 years or less. Nevertheless, the proportion of variance that the model explains is irrelevant.

Even if we add to the model the predictors related to familiarity of and experience with robots as well as interest in scientific discoveries, the model's output still does not change much. The statistically significant predictors remain the same, and the impact on the outcome variable of having more than 30 years of work experience compared with less than 10 years of work experience decreases only slightly. Indeed, the standardized beta is just -0.13 points.

The low values of the AIC and BIC coefficients indicate a model with better fit. According to these values, the personal level positive model and the societal level positive model including all predictors are the best models.

5. Discussion

A first consideration that can be drawn from this study of Italian health care workers is that the results of the exploratory factor analysis results correspond to the dimensions of the GAToRS scale, as identified by the researcher who first developed the scale (Koverola et al., 2022).

A second consideration relates to health care workers' general relationship with robots. Although robotics appears to be a familiar topic to health care workers and they express an overall positive view of them, the results show that they do not have a lot of personal experience of using robots. That health care workers have less experience of working with robots than the general population was also underlined by Turja et al. (2018) in the Finnish context. However, personal experience of robots does not influence the output of the regression models, and this contrasts with the other data in the literature which show that the amount of experience with robotic devices correlates with positive attitudes towards robots (Turja et al., 2018). While familiarity with robots influences people's sense of comfort around robots, it does not impact the social aspect of the scale used, and this finding should stimulate a deeper analysis of the implications at the social level.

On the other hand, the high level of interest, expressed by health care workers, in scientific discoveries and technological developments related to robots could be a factor that will contribute to developing the acceptance of social robots in the future. In fact, this variable has significant positive effects on the personal positive level and on the positive societal level of the GAToRS dimensions.

Another observation that emerges from the results is that, in this sample, the gender of health care workers was not relevant to attitudes towards social robots, contrasting with previous literature (Carradore, 2022; Turja et al., 2018). As far as the education dimension is concerned, the results show that a higher level of education impacts the positive social dimension more than having only secondary school education. This aspect confirms the results achieved in previous empirical research (de Graaf and Ben Allouch, 2013; Turja et al., 2018).

The area of employment (social health care vs medical health care) does not appear to impact health care workers' attitudes towards social robots, whereas the sector of work does have an impact; specifically, working in the care home sector in particular, but also in local healthcare units, is associated with greater acceptance of social robots compared with working in the hospital context. These findings should be considered in light of those of Turja et al. (2018), according to whom professionals in the medical field have generally positive expectations in relation to robotic aid, but only for specific activities; but, regrettably, a direct comparison is not possible due to the different nature of the variables and the data collected. This topic should be the subject of future investigations.

The years of work experience were also found to impact the acceptance of social robots, and the effect depended on the number of years and which dimensions of attitude are considered (Koverola et al., 2022). For instance, professional health care workers with more than twenty years of work experience are more likely to express unease and anxiety around robots than those who have been working for ten years or less; at the same time, rational hopes about robots were greater in those with more than twenty years of experience. The data do not permit deeper reflections on this aspect, but it would be interesting to investigate in more depth as it may have direct sociological implications. That is to say, considering the high workload placed upon health care professionals with many years of work experience, in combination with the ongoing growth in the ageing population (Cristea et al., 2020) and the shortage of workers (Michel and Ecarnot, 2020), this category of workers appears to be more open to accepting robots than workers with fewer years of experience.

To sum up, despite the small number of independent dimensions considered in this study, the results obtained appear to support the perspective that positive attitudes may help health professionals adopt social robots for care activities, as underlined by Chen et al. (2020).

6. Conclusions

The aim of this study was to investigate which sociodemographic and work factors influence health care workers' attitudes towards social robots considering the spread of this technology within the health care sector.

The main result identifies that confidence in social robots could improve individuals' and social acceptance of robots in health care workers. Some other questions related to the findings need to be addressed. One concerns the ethical aspects of the use of social robots in the health care setting at the national level. Experts in the field of sociology should contribute more to this debate by comparing their points of view with those from other disciplines, such as engineering, computer sciences, psychologists, and with experts in moral philosophy. The process should also involve public stakeholders as well as representatives of private organizations. Moreover, it might also be helpful to introduce this subject into the curricula of training programmes for health care professionals, in order that they may already be familiar with such technology before meeting it in the workplace.

Another important issue regards the high cost of robots, which limits their ubiquitous use. Resources of the Italian National Recovery and Resilience Plan should be devoted to this sector since it appears to be highly strategic for the future.

It is also important to remember that while this study focused on the attitudes of health care professionals, there is the point of view of the patients to consider. Thus, empirical data are required at the national level to develop insights into patients' views about robotics. The notion that robots stand to replace some aspects of caregivers' work is also important to consider and investigate (Kyrarini et al., 2021).

Finally, this research has some limitations. The first concerns the sample which is not representative and concentrates on just one developed area of Italy. Thus, further research should be performed to identify a larger, more representative Italian sample that takes into account a wider geographical area compared with this study, which focused on one specific area. Another limit concerns the nature of the sociodemographic and work variables used, especially those related to workers' age and number of years of work experience. A categorical format was applied in the present study, but future research should consider other formats.

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