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When do individuals choose care robots over a human caregiver? Insights from a laboratory experiment on choices under uncertainty

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ABSTRACT

Demographic changes and a predicted shortage of nursing staff are progressively putting pressure on the healthcare system. Care robots may represent one part of a possible solution to this problem as they can assist care work. However, large parts of the population are reportedly skeptical about robotics in care, and field studies are difficult to conduct due to the low prevalence of real robotics in the field. Therefore, we follow an experimental approach pertaining to the question of individual decision-making. In this regard, we analyze the aspects that influence the individual's choice between a care robot and a human caregiver for assistance in their daily life. Our economic experiment is conducted in a virtual laboratory to examine specifically how quality uncertainty of care affects individual's decisions for and against robotic care. In the experiment, 162 participants fully completed the experiment in which they were asked to repeatedly choose between a human caregiver and a care robot. Our results reveal that, overall, the care robot is chosen more often than a human caregiver. At the same time, the quality uncertainty of care linked to a human caregiver barely affected the choice of participants. On the other hand, a participant's health status and their attitude toward direct interactions with care robots did partially affect their choice. Additionally, we explored causes for indecisiveness and its effect on the choice. Here, we found indecisive participants tending to choose a human caregiver more often.

1. Introduction

Especially in western societies, demographic change and a predicted shortage of nursing staff will continue to put pressure on the healthcare system (Kis et al., 2017; Layte, 2009; Mielczarek, 2020; Super, 2002). Between 2010 and 2019 alone, in the population of the EU-28, the share of adults above 65 years of age grew from 17.5 percent to a predicted 20.0 percent (Eurostat, 2020). Projections by Eurostat indicate that the share will continue to expand to as much as 28.1 percent by 2050 (Eurostat, 2014). Following this imminent demographic change, the demand for long-term care services in the EU is expected to increase (Costa-Font et al., 2008; Kis et al., 2017).

Advancements in robotics for healthcare settings or assistance in general can be expected including technologies that can support older adults in their homes (Stone et al., 2016). One of these technologies is care robots. They are developed to assist human caregivers or directly support patients in their homes. As a result, care robots can be considered as a solution to the upcoming demographic change and the consequently increased need for caregivers. Utilizing this technology could relieve the healthcare system significantly (Bush, 2001; Mann et al., 2015). Despite the promising growth potential in the field of robotics (Keisner et al., 2015), most existing care robots are not ready to be fully implemented as they are not yet reliable enough to carry out care tasks independently (Bouwhuis, 2016). A study by Bedaf et al. (2015) identified 106 different types of care robots of which only 6 were successfully employed and available on the market.

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One crucial barrier for a successful implementation of care robots seems to be their acceptance among clients/patients and future users (Marakhimov & Joo, 2017). According to a survey conducted by Continentale (2019a), 60 percent of the participants stated that they would not approve of being treated by a care robot at home even if they required care. The main concern responsible for rejecting care robots was the furthered reduction of human contact, as well as a prevalent fear that the care robot might make mistakes due to technology malfunctions (Continentale, 2019b). The European Commission (2015) revealed a tendency that people with a more positive view of robots are likely experienced with them first-hand (European Commission, 2015). A lack of experience, on the other hand, causes uncertainty about the quality of the care provided. This quality uncertainty slows down the adaption of robotics. Accordingly, the field faces a negative re-enforcement spiral in which quality uncertainty leads to the avoidance of experimentation and less experience which, in turn, leads to quality uncertainty. To disentangle this process, we investigate the link between quality uncertainty and choice to deploy robotic assistance in an experimental setting.

In this paper, we are going to further explore the acceptance of individuals toward the usage of care robots and which factors influence their beliefs. In order to do so, a forced-choice experiment was conducted in which participants had to choose between a care robot and a human caregiver while being in need of care over the course of multiple days.

The paper continues as follows: Firstly, we introduce the experimental design and the methodical approach. Secondly, we analyze previous literature regarding the acceptance of care robots and, from our findings, derive hypotheses. Afterward, the results of the experiment are presented, and we evaluate the hypotheses. Finally, we discuss our results to draw conclusions and provide notes for further research.

2. Theory

In the following, we present previous literature regarding the acceptance of robots in health care and assistance in everyday activities and, accordingly, derive our hypotheses. Within the first hypothesis, we focus on whether people would choose a care robot or a human caregiver when requiring care.

Kachouie et al. (2014) conducted a literature review on care robots, aiming to compile a report on the state of the art in the field. They found that care robots have the potential to improve the well-being of older adults while decreasing the workload of health care workers (Kachouie et al., 2014). However, the integration of care robots into the health care system involves a range of challenges, including the acceptance of care robots by current and potential future users (Pino et al., 2015). Patients have varying preferences and expectations that need to be considered when developing and introducing new technology (Schäfer et al., 2019). Therefore, a care robot needs to be customizable and highly flexible to satisfy the demand of all patients (Pino et al., 2015). Meanwhile, technological restrictions prevent certain modifications and hinder the customizability and flexibility of a robot (Broadbent et al., 2009). By comparing a care robot to a human caregiver, one example for such a technological restriction lies within the lack of social and emotional components of a robot, e.g., their inability to perform proper facial expressions (Breazeal & Brooks, 2005, pp. 271–310; Hameed et al., 2016; Song & Yamada, 2017). This impairs the interaction between humans and robots, entailing that care robots in general fall short when aiming to imitate the complexity of a human-to-human interaction (Hameed et al., 2016).

Additionally, ethical issues regarding the implementation and usage of care robots need to be addressed to further explore the acceptance among potential users. Older adults may already face circumstances of a reduced social life and human contact (Sharkey & Sharkey, 2012; Wu et al., 2014). In this case, care from human nursing staff provides valuable human contact whereas the use of a care robot neglects it (Sharkey & Sharkey, 2012). A study by Continentale (2019b) found this potential reduction in human contact to be a major concern among individuals regarding the use of care robots. On the other side, having a care robot at home means that the caregiver is always present—unlike a human caregiver. However, this might result in a loss of privacy (Sharkey & Sharkey, 2012). Additionally, technological malfunctions might cause the robot to make mistakes, which is considered another major concern by individuals (Continentale, 2019b). When the person in need of care is in full control of the care robot and the commands given to it cause damage, the question arises of who should be held accountable (Sharkey & Sharkey, 2012).

We must also take into account the current state of robotics in healthcare. A major focus lies in its research and development. Hence, its potential is regarded as overwhelmingly positive among stakeholders (Gelderblom et al., 2009). However, robots are still far from being well established in the healthcare industry (Azeta et al., 2017; Gelderblom et al., 2009). Not all research and development so far has been a success, and care institutions tend to be hesitant when adopting these technologies (Gelderblom et al., 2009). In a study conducted by Broadbent et al. (2012), various stakeholders, including managers, human caregivers, and residents, have shown a general lack of knowledge on how robots can be used in the care context. This is hugely problematic since human caregivers would be required to be knowledgeable enough to introduce the technology to the patients and explain the benefits to enhance both understanding and acceptance of care robots (Barnard et al., 2013; Gitlin, 1995; Johansson-Pajala et al., 2019, 2020). Examining the issues pertaining to direct interactions, as well as the ethical and structural problems, we expect a low acceptance toward care robots. Therefore, we hypothesize that when comparing human caregivers and care robots:

H1. Robots are chosen less likely as a caregiver than humans.

Contrary to Hypothesis 1, we will also explore the acceptance toward a human caregiver. In the process, we thus consider the quality uncertainty linked to a human caregiver since uncertainty in healthcare quality is a common issue (Han et al., 2011). Accordingly, within our study, we differentiate between two different aspects of quality certainty: care robots and human caregivers. A human caregiver holds many advantages over a care robot as discussed regarding Hypothesis 1. However, robots are programmed to complete certain tasks and, as a result, are consistent in what they do (Bringsjord, 2008). On the contrary, a human caregiver represents an element of uncertainty as their behavior can be complex and unpredictable (Okamura et al., 2010). Mishel (1981) developed the Mishel Uncertainty in Illness Scale and analyzed the correlation between perceived uncertainty and a patient's stress level. His findings imply that uncertainty results in a higher stress level (Mishel, 1981, 1984). These results are further supported by more recent studies. For example, Madar and Bar-Tal (2009) found uncertainty to be the best predictor of patients' stress levels, even outperforming their own perceived health status. Since patients will try to reduce their stress level, we expect the quality uncertainty linked to a human caregiver to influence their choice. Therefore, we hypothesize that:

H2. The likelihood that a human caregiver is preferred over a care robot depends on the quality uncertainty of the human.

In the following two hypotheses, we emphasize factors that may influence the beliefs of a patient and their choice between a care robot and a human caregiver. One focal point is the effects of the health status of a patient and their attitude towards characteristics of a robot within direct interactions as both of these factors have been identified as crucial for the choice and acceptance of a patient.

Care robots involve the challenge of working in the health care setting and thus being surrounded by vulnerable individuals due to their health status. As a result, when developing and implementing care robots, great importance is attached to the robot's reliability to ensure the patients' safety (Khan & Anwar, 2019; Schwiegelshohn et al., 2017). Considering the focus on reliability and safety, we do not expect patients with a worse health status to be less acceptant toward care robots.

Furthermore, individuals who require care are more likely to seek out care options including the use of a care robot as it can secure a higher degree of independence by enabling them to stay at home longer (Schwiegelshohn et al., 2017). This argument is further supported in a study by Pino et al. (2015) in which persons with mild cognitive impairments found care robots more useful and thereby showed greater intention to employ them than healthy older adults. Therefore, we hypothesize that:

H3. Participants with a worse health status are more likely to choose a care robot.

Healthcare services and care, in general, include direct interactions and communication with patients. Care robots lack certain social and emotional skills within these interactions, as seen, e.g., in their inability to perform proper facial expressions (Breazeal & Brooks, 2005, pp. 271–310; Hameed et al., 2016; Song & Yamada, 2017). As a result, robots are widely unable to match the complexity of human-to-human interaction (Hameed et al., 2016). In this regard, direct interactions between a patient and a care robot are seen as one of the most important concerns when furthering the acceptance of care robots (Kuo et al., 2009; Moradi et al., 2018). Meanwhile, the preference and attitudes of individuals toward care robots vary. For example, studies show that patients who are concerned about these social issues prefer a humanoid care robot due to its human-like appearance (Hameed et al., 2016; Moradi et al., 2018). Nomura et al. (2006) developed the Negative Attitude toward Robot Scale (NARS) focusing on the varying attitudes of individuals toward robots and their effect. They found that individuals with a higher negative attitude toward robots tended to avoid direct interactions with them altogether (Nomura et al., 2006, 2008). Therefore, we expect the attitude of individuals toward direct interactions with robots to affect their preferred form of care and hypothesize that:

H4. Individuals with a higher negative attitude toward direct interactions with robots are less likely to choose a care robot.

Additionally, this study investigates the indecisiveness of a patient and the correlation to the acceptance of care robots. The acceptance towards care robots depends on the information accessible to its stakeholders, as well as their knowledge on how robots can be used in the care context (Broadbent et al., 2012; Gitlin, 1995). In a scenario in which a patient lacks information and knowledge on how a care robot could assist them, the human caregiver should be able to provide information on the benefits of a care robot (Gitlin, 1995). However, as revealed in a survey by Broadbent et al. (2012), even stakeholders, including managers, caregivers, and residents, have shown a general lack of knowledge on robots in the context of care work. Consulting research on decision-making, a lack of information hinders the decision-making process and promotes indecisiveness (Germeijs & De Boeck, 2003; Rassin, 2007). This implies that a lack of information on robots in the context of care leads to patients being indecisive when choosing between a care robot and a human caregiver. If patients lack information about care robots, they are unfamiliar with them, resulting in uncertainty (Mishel, 1984, 1988). While a human caregiver also includes an element of uncertainty, it is a form of care with which patients are more familiar. According to the study conducted by Hackett and Cassem (1975), the unfamiliarity of surroundings is considered one of the most stressful events according to patients. Therefore, we expect that reducing the unfamiliarity with care robots by providing further information would promote their acceptance in the care context. This is further supported by literature on the expectations and perceptions of older adults, which underlines that dissemination of information on how robots can assist in care may change the mind of older adults in favor of a care robot (Hoppe et al., 2020). Considering that we expect a lack of information on care robots to further promote indecisiveness we hypothesize that:

H5. Patients that are indecisive in their decision between a care robot and a human caregiver will tend to prefer a human caregiver.

3. Methods

We executed a forced-choice experiment in which the participants were told that they required care and should choose between a human caregiver and a care robot. As we are especially interested in the effects of quality uncertainty and choice, participants did not know the quality of the care provided in advance. Additionally, we implemented different treatments with different degrees of quality uncertainty. Based on this study design, we aim to test our hypotheses and draw a conclusion regarding the general acceptance and decision-making in favor of or against care robots.

3.1. Participants

In total, 162 individuals participated. 105 of the participants are male and 57 are female. The participants' age averages at 31.2 years (with a standard deviation of 9.8, range 17-67 years). The participants come from five different home countries: 55 from Italy, 53 from the United Kingdom, 32 from Spain, 14 from Germany, and 8 from France. No further limitations or previously assumed knowledge levels on human caregivers or care robots applied regarding the participation in the experiment.

Participating in the experiment took about 10 min. For fully completing the experiment, participants earned between 3.06 and 3.96 Dollars with an average earning of 3.50 (and a standard deviation of 0.13). Thereby, participants earned 0.05 Dollars per experimental unit during the experiment plus an additional 0.01 Dollars.

3.2. Setting

We programmed a choice experiment in oTree (https://www.otree.org/). The experiment itself took place on the online platform Amazon Mechanical Turk (MTurk)—an online crowdsourcing platform—between February and April 2020. MTurk is a crowdsourcing website allowing businesses to hire remotely located "crowdworkers" to perform discrete on-demand tasks. For these tasks, workers earn a payment afterward, e.g participating in an experiment.

Usually, research mentions some limitations with MTurk samples which we try to circumvent with our procedures: First individuals may participate who do not understand the questions (Smith et al., 2016). In our study, we have chosen only to allow participation from Europe which may limit the tendency to just click anything. Moreover, we have incentivized the task which also limits the randomness of choices. Recent research shows that these samples also have some strength such as a more diverse population (Buhrmester et al., 2018) resulting in mean results close to other survey types (Levay et al., 2016).

3.3. Procedure

At the start of the experiment, the participants received a written explanation of the experiment's setting. They were asked to imagine that they were injured for the upcoming 10 days and needed help with everyday activities (including dressing, eating, and cleaning). Each day, they would have to choose 1) to employ a human caregiver for 1 h or 2) rent a care robot for the whole day. For each day, participants receive experimental units that may differ depending on their choice between a human caregiver and a care robot. Finally, participants were asked to fill in a short questionnaire, including questions regarding their health status and technology orientation using the Negative Attitude Towards Robot Scale introduced by Nomura et al. (2006). For the introduction to the experiment given to the participants, refer to Appendix A.

3.4. Experimental design

For the experiment, the participants are endowed with an experimental currency unit which was later converted to their respective currency. In order to exclude effects stemming from currency differences, we use the artificial currency of “Tokens”.

At the beginning of the experiment, every participant was endowed with 100 Tokens. The daily costs for a human caregiver and a care robot both amount to 10 Tokens. The chosen form of care results in a level of satisfaction among the participants. In this regard, the satisfaction ranges between 0 and 10 for each day. For every level of satisfaction, the corresponding number of tokens is added to the participant’s account. The exact levels of satisfaction for every round of the experiment were defined prior to the experiment and, thus, do not depend on the participants themselves. Additionally, the respective satisfaction levels of a care robot and a human caregiver are unknown to the participants before making a choice. Only after their choice, they were informed about their achieved satisfaction level in each round. Hence, over the rounds of the experiment, participants were able to discover the rates according to their choices and the feedback concerning their satisfaction levels.

For our experimental design, we assume that care robots are consistent in what they do and fulfill the same tasks every day. Consequently, they will generate the same level of satisfaction every day. Since the human caregiver may vary from day to day, there is a certain level of uncertainty about the quality of care. Therefore, the satisfaction level of the participants with the caregiver services may also vary from day to day.

The care robot’s satisfaction level was set at 7 for the participant. Accordingly, in every round the care robot was chosen, the participant earned 7 Tokens.

The satisfaction level with a human caregiver varies over the rounds of the experiment. They were exogenously ex-ante determined and unknown to the user. Thus, for the user, the decision was under uncertainty, and the satisfaction level was experienced only after each decision had been made. For this purpose, the participants were randomly assigned to one of the four treatments in the experiment. In each treatment, the mean satisfaction level equals 7, but the variation of the satisfaction level differs among the treatments. In Treatment 1 and 2, the human caregiver results in a satisfaction level between 6 and 8 units. Here, Treatment 1 starts with a low satisfaction level of 6 units whereas Treatment 2 starts with a high satisfaction level of 8 units. In Treatment 3 and 4, the variation of the satisfaction level ranges from 4 to 10. Treatment 4 starts with a low satisfaction level of 4 units while Treatment 3 starts with a high level of satisfaction of 10 units. Thus, we differentiate a low-quality first experience (treatment 1 and 4) and a high-quality first experience with the human caregiver (treatment 2 and 3), as well as low variance in quality (treatment 1 and 2) and high variance in quality (treatment 3 and 4). Table 1 displays the varying levels of satisfaction for each of the four treatments. Additionally, a visualization of the procedure of the experiment is available in Appendix B.

As we are only interested in the influences of service quality uncertainty, we held other potential influences such as likeability of the human or the robot constant and did not show any pictures. In both cases, pictures or videos may result in very artefact specific results, e.g. when the robot is particularly cute (or not) or the human caregiver seems to be likeable (or not).

3.5. Description of variables

Dependent variables

The main dependent variable in our experiment is the choice between a care robot and a human caregiver in each round represented by the number of times the care robot is chosen by the participant. Based on this variable, we further deviate. We consider participants as indecisive if they have no clear tendency toward either a care robot or a human caregiver. To review the indecisiveness of a participant, we consider the number of times a participant switches between the two choices and a dichotomous variable ‘Evenly balanced choice’ representing whether a participant chooses the care robot in 40–60 percent of the rounds (Table 2).

Independent variables

The main independent variable within our experiment is the quality uncertainty linked to a human caregiver. As shown in Table 1, this quality uncertainty varies depending on the assigned treatment. In the process, we include age, gender, and satisfaction level of a participant as control variables. The satisfaction level is cumulated over the whole experiment and depends on the assigned treatment and the choice between a care robot and a human caregiver in each round as depicted in Table 1.

Additionally, we consider independent variables that may influence the choice between a care robot and a human caregiver to some extent. In this regard, a person’s health status can be considered since those requiring care due to poor health are more likely to seek care options (Schwiegelshohn et al., 2017). Therefore, we include the health status as a categorical variable with answers varying between ‘Not good’ and ‘Very good.’ Additionally, we consider the attitude of participants toward robots. To measure this attitude toward technology in general and care robots in particular, we applied the Negative Attitude Towards Robot Scale introduced by Nomura et al. (2006). It includes 14 items with three corresponding factors as represented in Appendix C. A confirmatory factor analysis for our experiment shows that the factor structure consists of the same three factors as suggested in previous research. Moreover, the model has the following goodness-of-fit indices:

Table 2
Description of dependent variables.

Dependent variables	Percentage	Min	Max	Mean	Std. dev.	N
Number of times the care robot is chosen by a participant		0	10	5.938	2.837	162
Number of times a participant switches between the two choices		0	9	3.284	2.358	162
Evenly balanced Choice		0	1	0.370	0.484	162
A Participant chooses the care robot in 40–60 percent of the rounds (1)	37.04					60
Else (0)	62.96					102

Table 1
Satisfaction levels.

Rounds	1	2	3	4	5	6	7	8	9	10	Number of Participants
Care Robot	7	7	7	7	7	7	7	7	7	7	
Treatment 1: Negative Start & Low-Quality Variance (NSLV)	6	7	8	7	6	7	8	7	6	7	43
Treatment 2: Positive Start & Low-Quality Variance (PSLV)	8	7	6	7	8	7	6	7	8	7	42
Treatment 3: Positive Start & High-Quality Variance (PSHV)	10	7	4	7	10	7	4	7	10	7	39
Treatment 4: Negative Start & High-Quality Variance (NSHV)	4	7	10	7	4	7	10	7	4	7	38

Note: The table represents the satisfaction level when choosing either a care robot or a human caregiver (depending on the assigned treatment) in any round of the experiment.

CFI = 0.865, RMSEA = 0.091 and SRMR = 0.069, implying a high quality of the model (Table 3).

4. Results

In the following, we are going to represent the results of the experiment. In the process, we evaluate Hypotheses 1 and 2 in the first part when discussing the descriptive results of the experiment. Afterward, we examine influential factors and concomitantly answer Hypotheses 3 and 4. Finally, we provide a more in-depth discussion of uncertainty and, in the course, address Hypothesis 5.

4.1. Descriptive results

To analyze the distributed preference between a human caregiver and a care robot in our experiment, we first observe the choices made in every round over all treatments. Fig. 1 depicts the relative number of participants that chose a care robot in each round.

Throughout the experiment, the care robot was chosen on average 59.02 percent of the time. When examining each round individually, the percentage varies between 55.21 and 64.42. Hence, the care robot is chosen more frequently than the human caregiver in every round. Hypothesis 1 predicted the human caregiver to be selected more often than a care robot. As proven, this is not the case, and Hypothesis 1 can be rejected.

Additionally, the participants of the experiment were randomly assigned to one of four treatments varying in quality. Thus, we introduced quality uncertainty to the experiment. With each treatment varying differently in quality throughout the experiment, each also represents a different level of quality uncertainty. Fig. 2 shows the average number of times a care robot was chosen throughout the experiment differentiated by the four treatments.

Comparing the choice for each treatment individually, Fig. 2 highlights that, throughout the experiment, the care robot was chosen on average 5.511 times by participants with the assigned treatment NSLV, 6.071 by participants with the treatment PSLV, 5.795 by participants with the treatment PSHV, and 6.421 by participants with the treatment NSHV. For all four treatments, the care robot was on average selected more often than the human caregiver. However, the percentage of choosing a care robot varies between 55.12 and 62.56 percent depending on the treatment (Fig. 2). In order to test whether these differences are significant, we performed a pairwise comparison between all the treatments while considering all rounds of the experiment using a Wilcoxon-Mann-Whitney-Test. As shown in Appendix D, there is no significant difference between any of the treatments regarding the choice for a care robot when considering all rounds of the experiment.

Additionally, we sought to observe the effect of the treatment in each round individually. In doing so, we first visualized the choice of a care robot for each round differentiated by treatment in Fig. 3. Afterward, we applied a chi-squared test and Fisher's exact test to assess whether there are significant differences between the treatments.

As shown in Appendices E and F, the treatment assigned to a person has a significant effect on the choice in the 4th, 7th, and 9th round according to the chi-squared test and Fisher's exact test. Appendix G highlights the deviations regarding the different treatments for these rounds. In rounds 4 and 9, participants with the NSLV treatment have chosen the care robot significantly less often than participants with a different treatment. Contrastingly, in the 7th round, participants with the PSHV treatment have chosen a care robot significantly more often than participants with a different treatment. Additionally, the chi-squared test reveals that participants with the second treatment (PSLV) selected a care robot significantly more often in the 4th round.

Hypothesis 2 predicted the quality uncertainty of a human caregiver to affect how often the human is chosen. In our experiment, each treatment represents a different level of quality uncertainty linked to a human caregiver. Considering that the treatment only has a significant effect on the choice of a care robot or a human caregiver in a few individual rounds, Hypothesis 2 must be rejected.

4.2. Influencing factors on the choice and preference of the participants

In the following, we will construct a regression model to reveal influencing factors on participants' choice for a care robot. According to Hypotheses 3 and 4, we expect the health status, on one hand, and the attitude toward social and emotional components of a robot, on the other hand, to have a significant effect on the choice. We focus on a Tobit regression analysis, the dependent variable being the number of times a care robot is chosen throughout the experiment by a participant. This is represented in Table 4. In the first model, we only include the explanatory variables 'Health Status' and 'Technology Orientation' while, in the second model, we add control variables.

According to the Tobit regression model in Table 4, a participant's health status has a significant effect on the choice between a care robot and a human caregiver. Participants that perceive their health status as 'Not Good' chose a care robot on average significantly less often than participants that perceive their health status as 'Good.' When considering the technology orientation, the only item of the NARS by Nomura et al. (2006) that has a significant effect on the choice between a human caregiver and a care robot is 'Negative attitude toward emotions in interaction with robots' in the first model. Hence, a higher negative attitude is associated with choosing a care robot less often.

Examining the results depicted in Table 4, we can evaluate Hypotheses 3 and 4. According to Hypothesis 3, participants with a worse health status were expected to choose a care robot more frequently This hypothesis must be rejected as the contrary can be observed in Table 4 and Appendix H.

Hypothesis 4 stated that a higher negative attitude toward social and emotional components of a care robot reduces the likelihood of choosing a robot for care work. This hypothesis can be partially accepted. The attitude toward emotional components seems to disfavor the choice for a care robot, considering that a higher 'negative attitude toward emotions

Table 3
Description of independent variables.

Independent variables	Percentage	Min	Max	Mean	Std. dev.	N
Treatment						162
NSLV	26.54					43
PSLV	25.93					42
PSHV	24.07					39
NSHV	23.46					38
Age		17	67	31.228	9.804	162
Gender		0	1	0.352	0.479	162
Male (0)	64.81					
Female (1)	35.19					
Satisfaction Level		61	79	69.796	2.593	162
Health status		1	4	3.204	0.765	163
Not good (1)	1.85					3
Satisfactory (2)	15.43					25
Good (3)	43.21					70
Very good (4)	39.51					64
Technology Orientation						
Negative attitude toward situations of interaction with robots		1	5	2.683	0.939	162
Negative attitude toward social influence of robots		1	4.8	2.922	0.718	162
Negative attitude toward emotions in interaction with robots		1	4	2.224	0.690	162

Note. **NSLV:** Negative Start & Low-Quality Variance, **PSLV**: Positive Start & Low-Quality Variance, **PSHV**: Positive Start & High-Quality Variance, **NSHV**: Negative Start & High-Quality-Variance.

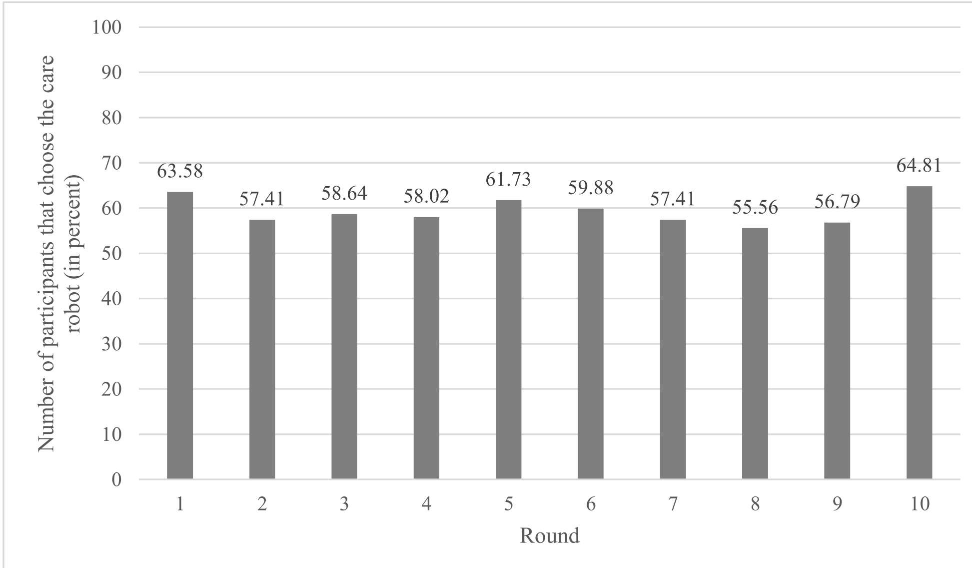

Fig. 1. Relative number of participants choosing a care robot in each round.

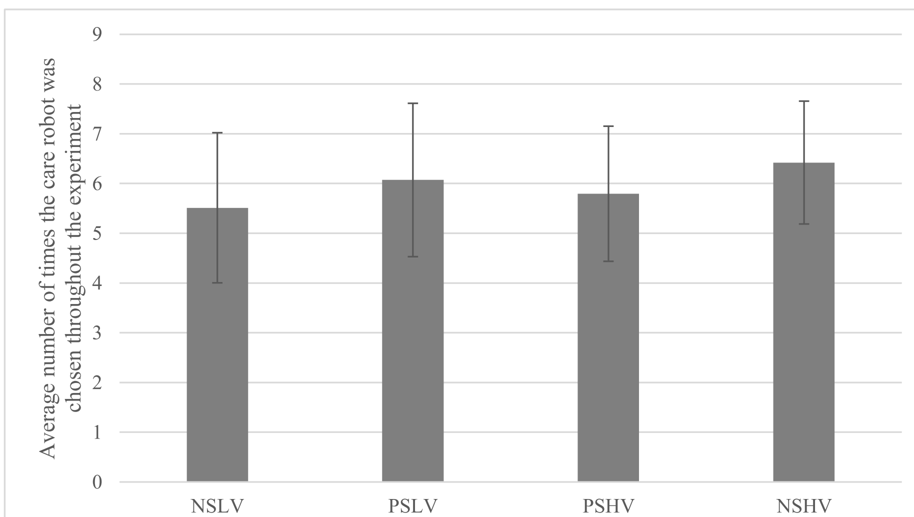

Fig. 2. Average number of times a care robot was chosen differentiated by treatment
Note. **NSLV:** Negative Start & Low Quality Variance, **PSLV**: Positive Start & Low Quality Variance, **PSHV**: Positive Start & High Quality Variance, **NSHV**: Negative Start & High Quality Variance.

in interaction with robots' was found to reduce the likelihood of choosing a care robot. However, it must be noted that the items focusing on robot interactions in general, as well as on the social influence of robots in particular, have no significant effects on the choice of a care robot within our data-set. Thus, an effect of attitude toward social components of a robot toward the likelihood of choosing a care robot cannot be proven.

4.3. *Uncertainty regarding the choice between a care robot and a human caregiver*

We consider participants indecisive if they exhibited no clear tendency for choosing either a care robot or a human caregiver in everyday assistance. We operationalized indecisiveness with the number of times participants changed their choice in consecutive rounds throughout the experiment and by building a dichotomous variable 'evenly balanced choice' representing whether a participant chooses a care robot in 40–60 percent of rounds.

To test whether the indecisiveness of a participant influences how often the care robot is chosen, we first tested for a correlation between them, as seen in Table 5.

Table 5 depicts the correlation between choosing a care robot and being indecisive represented by the number of times a participant switches between the two choices and whether a participant exhibited an evenly balanced choice pattern. Both aspects representing indecisiveness have a significant negative correlation with choosing a care robot over a human caregiver. Therefore, participants that change their choice more often throughout the experiment or choose evenly, on average preferred the human caregiver. To further analyze these correlations, we showcase the choice for a care robot depending on whether the participant shows an evenly balanced choice pattern. As illustrated in Appendix I, the care robot is chosen on average in 59.02 percent of the rounds by all participants, while participants with an evenly balanced choice selected the care robot on average in only 48 percent of the rounds (standard deviation of 7.983). Additionally, participants with an evenly balanced choice pattern decided on a care robot less often than

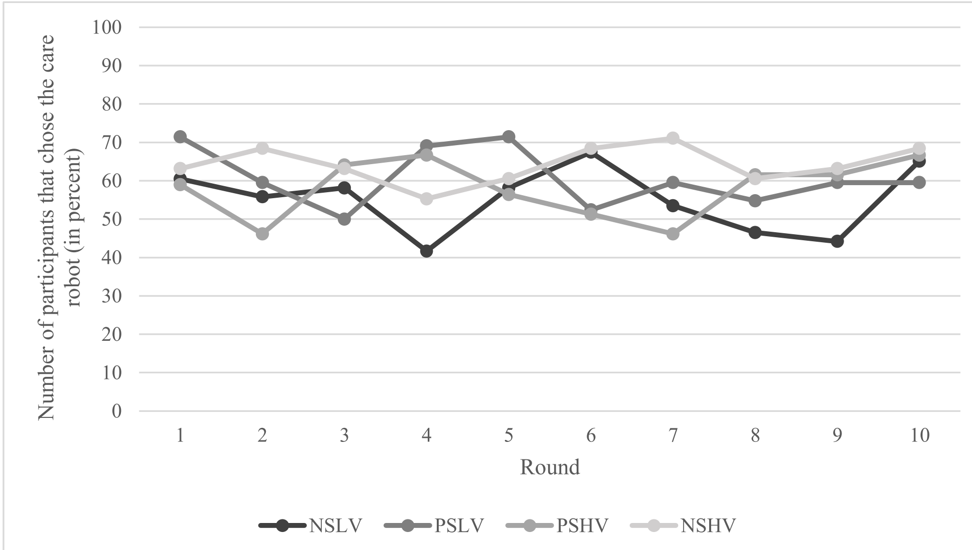

Fig. 3. Relative number of participants that choose a care robot differentiated by treatment for each round.
Note. **NSLV:** Negative Start & Low Quality Variance, **PSLV**: Positive Start & Low Quality Variance, **PSHV**: Positive Start & High Quality Variance, **NSHV**: Negative Start & High Quality Variance.

Table 4
Tobit regression model on the number of times a care robot is chosen.

	(1)	(2)
Treatment [Ref.=NSLV]		
PSLV (2)		0.671 (0.735)
PSHV (3)		−0.010 (0.784)
NSHV (4)		0.756 (0.756)
Age		−0.014 (0.028)
Gender [Ref.=Male]		−0.146 (0.563)
Satisfaction level		−0.028 (0.105)
Health Status [Ref.=Good]		
Not Good (1)	−6.478*** (2.182)	−6.289*** (0.037)
Satisfactory (2)	−0.919 (0.751)	−0.868 (0.765)
Table 4 *continued*		
Very Good (4)	0.069 (0.573)	0.143 (0.487)
Negative Attitude towards Robots Scale		
Negative attitude toward situations of interaction with robots	−0.473 (0.381)	−0.443 (0.392)
Negative attitude toward social influence of robots	−0.302 (0.499)	−0.406 (0.514)
Negative attitude toward emotions in interaction with robots	−0.826* (0.485)	−0.764 (0.487)
Constant	10.444*** (1.201)	12.601* (7.502)

Note. Negative Attitude towards Robot Scale by Nomura and Kanda (2016), **NSLV:** Negative Start & Low-Quality Variance, **PSLV**: Positive Start & Low-Quality Variance, **PSHV**: Positive Start & High-Quality Variance, **NSHV**: Negative Start & High-Quality-Variance, Gender (0 = Male, 1 = Female), Health Status (1 = Not Good, 2 = Satisfactory, 3 = Good, 4 = Very Good), Standard error in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

participants without such an evenly balanced choice. This holds for every round of the experiment as displayed in Appendix J.

According to Hypothesis 5, we expected indecisive participants to choose a human caregiver more often than the remaining participants. We operationalized the indecisiveness of a participant with the number of times participants change their choice in consecutive rounds throughout the experiment and whether they exhibited an evenly balanced choice pattern or not. We found indecisiveness to be associated with choosing a care robot less often. As a result, Hypothesis 5 can be accepted.

Table 5
Correlation between choosing a care robot and being indecisive.

	Number of times a participant switches between the two choices	Evenly balanced choice	Number of times a care robot is chosen
Number of times a participant switches between the two choices	–	0.593***	−0.376***
Evenly balanced choice		–	−0.309***
Number of times a care robot is chosen			–

Note. **Evenly balanced choice**: 1, if a participant chooses a care robot in 40–60 percent of the round, else 0. *** p<0.01, ** p<0.05, * p<0.1.

5. Discussion

This paper aimed to analyze the acceptance of individuals toward the use of care robots when requiring help in everyday life. Examining the results, one can notice that, contrary to our initial considerations, a care robot is chosen more often than a human caregiver. This represents a constant throughout the experiment, the care robot being selected at least 10 percentage points more often than the human caregiver in every round. Previous research discussed issues within direct interactions with care robots. Based on these findings, we expected a care robot to be chosen less frequently than a human caregiver. According to Hameed et al. (2016), robots in general still lag when seeking to emulate the complexity of human-to-human interaction. However, depending on the intended purpose of the robot, striving to imitate this complexity might not be required to begin with. For example, assisting with taking medications, delivering meals, or cleaning are potential tasks for which a care robot can be designed (Carreira et al., 2006; Datta et al., 2011; Forlizzi, 2007) that do not rely on complex direct interaction. Within our experiment, participants were instructed that they would, amongst other things, need help with dressing, eating, and cleaning. These tasks fall under such that do not require complex direct interactions, thus potentially explaining why the care robot was as popular in our experiment despite its shortfalls within direct interactions. Additionally, even if a direct interaction takes place, designing it in a way that is acceptable for the patient is possible. The care robot Zora, for example, relies on direct interactions to facilitate exercise. However, due to its child-like design and calm behavior, users do not report any negative impacts of the interaction (Melkas et al., 2020).

Further research revealed that, despite the focus on robotics in healthcare in recent studies and the advances the field has recently made, there still exist structural issues to overcome (Broadbent et al., 2012; Gelderblom et al., 2009). On the one hand, providers seem to hesitate when adopting new technologies and offering them as a service (Gelderblom et al., 2009). On the other hand, consumers are often ill-informed about the benefits of care robots (Broadbent et al., 2012). Within our experiment, however, we reduced these structural issues by offering individuals the option to choose a care robot to begin with. Additionally, they received information about the tasks the care robot would be able to perform. Therefore, one reason for the high acceptance toward care robots within our experiment may have been attributed to the reduced structural issues.

Within our experiment, participants were randomly assigned to one of four treatments. Each treatment represents a different form of quality uncertainty. However, the treatment, as well as the quality uncertainty it entailed, only affected the choice of a participant to a limited extent, a significant effect only being observed in three of the ten rounds. This contradicts our initial considerations. According to Mishel (1981; 1984) and Madar and Bar-Tal (2009), uncertainty in a health care setting results in a higher stress level of the patient. As a result, we expected the uncertainty linked to the assigned treatment to influence the choice of a human caregiver. Within our experiment, we additionally included a second aspect of quality certainty with care robots. While robots, in general, are programmed to complete tasks and, as a result, are consistent in what they do (Bringsjord, 2008), care robots offer a form of care with which patients are less familiar. This unfamiliarity also leads to uncertainty (Mishel, 1984, 1988). Therefore, the quality uncertainty of a human caregiver might not affect the choice of participants as much as expected since the care robot also involves an element of uncertainty.

On the contrary, the health status of a participant did significantly affect their choice between a care robot and a human caregiver within our experiment. Participants that assessed their health status as 'Not Good' were found to choose a care robot significantly less often than participants that reported 'Good' health status. This contradicts a study by Schwiegelshohn et al. (2017) who argue that individuals with a worse health status have a more urgent need for care. Consequently, they are supposedly more likely to seek options for care, including the use of a care robot, as it can ensure a higher degree of independence by enabling them to stay at home longer. Accordingly, previous research focused on the reliability of care robots to ensure the safety of the patients (Khan & Anwar, 2019; Schwiegelshohn et al., 2017). However, individuals may not be aware of this focus. This could be explained by a general lack of knowledge on robots in the context of care (Broadbent et al., 2012). In that case, especially individuals with a worse health status have a reason to be concerned about care robots since they are more vulnerable if a robot malfunctions. After all, a care robot making a mistake due to a technological malfunction reportedly represents a major concern for individuals (Continentale, 2019b).

Additionally, the participants' negative attitude toward robots was found to partially affect the choice between a human caregiver and a care robot. To measure the negative attitude toward robots, we applied the Negative Attitude Toward Robot Scale (NARS) introduced by Nomura et al. (2006). Here, we found a higher 'negative attitude toward emotions in interaction with robots' to decrease the likelihood of selecting a care robot. On the other hand, the 'negative attitude toward situations of interaction with robots' and the 'negative attitude toward the social influence of robots' did not significantly affect the choice of participants within our experiment. In a study by Nomura et al. (2006) and Nomura et al. (2008), a higher negative attitude in any of the three aspects was found to correlate with a tendency of avoiding direct interactions with a robot. Considering that, within our experiment, direct interaction with a care robot is most easily avoided by simply choosing a human caregiver, we expected all three items to have a significant effect on the choice. However, it can be argued that participants that rank high on the 'negative attitude toward robot' scale might still choose a care robot as the required tasks of the care robot in this experiment do not require much direct interaction.

Lastly, we focused on indecisive participants that exhibited no clear preference for either a care robot or a human caregiver. According to our experiment, indecisive participants did tend to choose the human caregiver more often compared to decisive participants. This is in line with previous research. According to Germeijs and De Boeck (2003) and Rassin (2007), one cause of indecisiveness is a lack of information since it hinders the decision-making process. A general lack of information on how care robots can be applied can be observed (Johansson-Pajala et al., 2019), for example in the study by Broadbent et al. (2012), in which various stakeholders were unfamiliar with care robots. Moreover, Mishel (1984; 1988) finds that a lack of information further results in individuals being unfamiliar with robots in the care context. A human caregiver, on the other hand, provides a form of care with which people are much more familiar. A study by Hackett and Cassem (1975) ties into this as it demonstrates how unfamiliar surroundings are considered among the most stressful events according to patients. Thus, we can explain why indecisive participants within our experiment chose the care robot less often. In an attempt to increase the acceptance of individuals toward care robots, one could, consequently, disseminate information to familiarize potential users with the concepts.

5.1. Limitations

Regarding the limitations of our study, it should be noted that laboratory experiments can certainly not reveal actual deployment decisions since they lack external validity. Thus, the method is not suited to forecast real decisions. However, they are—due to their high internal validity—suited to disentangle and analyze factors theoretically relevant to decisions.

We assumed the satisfaction level with a care robot to be consistent within our experiment. However, care robots might malfunction one day, thus challenging this assumption. Furthermore, we set the expected quality of a human caregiver for each treatment on average about as high as the expected quality of a care robot. Whether this is a realistic assumption is debatable. As pointed out before, robots are not yet able to emulate the complexity of human-to-human interaction (Hameed et al., 2016). However, the field of robotics maintains a promising growth potential while further advancements in healthcare can be expected in the future (Keisner et al., 2015; Stone et al., 2016). Considering further technological advancements in healthcare, the quality of care robots can be expected to increase, thereby legitimizing the initial assumption of the expected quality of a care robot and a human caregiver to be equal. Furthermore, the expected quality of the care robot is only set to be about equal to and not higher than that of a human caregiver and, therefore, does not explain why the care robot is chosen at least 10 percentage points more frequently than the human caregiver throughout every round of the experiment.

Additionally, participants were not given the opportunity to interact with a care robot within our experiment. However, it must be noted that studies analyzing the acceptance of care robots have revealed the attitude toward care robots to become less negative after an initial interaction with them. This is attributed to the increased awareness of potential benefits the technology can offer for the participants' lives (Stafford, 2013; Stafford et al., 2010; Tsertsidis et al., 2019). Since participants did not interact with the care robot in our experiment, this effect is inapplicable. If such an interaction would have been provided, participants might have evolved a less negative attitude throughout the experiment. Considering that the negative attitude toward robots was found to partially affect the choice of participants within our experiment, it stands to argue that allowing such an interaction would have resulted in the care robot being chosen more often.

Moreover, we abstract from legal problems which certainly differ between human and robot caregivers and may also be perceived differently by the respondents in our experiment. Leenes et al. (2017) for instance lay out that in practice, liability costs of technology are frequently incorporated ex ante into the manufacturers cost function while this may not be the case when a human caregiver is involved. In our experiment, we simply state that there are differences in the utility, but less than expected utility may be associated with liability law in the eyes of a user. Therefore, differences in regulatory issues may cause an individual's tendency towards robots in our experiment even though we are trying to capture satisfaction and not legal issues. Future research should probably disentangle both. Moreover, the reference point for a comparison for the individuals in our experiment is a human caregiver, and therefore, the focal point of comparison is not utility or privacy issues with or without care, but a comparison given that there needs to be care. In that sense, legal considerations and evaluations may well differ from our analysis as the reference point is different (Fosch-Villaronga & Albo-Canals, 2019). Yet, the legal perspective on liability and the differentiation from satisfaction as well as privacy and the differentiation from individual private sphere is needed for a thorough evaluation.

Another limitation of our study is that given that there are personal considerations in effect, the situation and evaluation may also differ between individuals and between different groups of individuals, e.g. according to the health care system, the reliance on family members' care and alike. In societies in which elderly care is usually provided by professional nurses, for example, the acceptance of health care robots may be less likely compared to a situation in which family members are informal caregivers and older adults may be more likely to feel being a burden to them. In our study, we have primarily focused on Western societies and the respondents in our sample stem from Europe. In different health care systems, and in different family structures, respondents' answers may differ. Alike, the inclination of accepting a robot may also vary between health care systems and for instance depend on whether health care is equal or not. In some countries, robots may be only available to the rich while in other countries, robots may be only available to the poor depending on labor costs and health care funding system.

5.2. Future research

The acceptance toward care robots further depends on factors not included in our experiment. The appearance of a robot, for example, is expected to greatly affect the acceptance rate, with individuals being less accepting of robots with a human-like appearance and behavior (Appel et al., 2020; Mori, 1970). This is further supported by a survey by Arras and Cerqui (2005, p. 605) in which only 19 percent of the participants preferred a robot with a human-like appearance. These findings suggest that the care robot's design must match an individual's preference as well as the required task (Broadbent et al., 2012; Pino et al., 2015). Therefore, the importance of customizing the appearance of a care robot depending on the individual's preference should be emphasized (Pino et al., 2015). Future research could, therefore, focus on how the results of our experiment would change if the appearance of the robot was specified. One could, for example, assign a different appearance to each treatment and explore how this affects the choice. Alternatively, participants could be offered a variety of appearances of a robot when choosing a care robot to explore whether this option increases the choice for a care robot and which appearance is most popular among participants.

6. Conclusion

The imminent demographic changes represent a considerable challenge for the healthcare system since the need for healthcare workers and nursing staff is expected to increase. Additionally, this might further advancements in healthcare regarding diagnostics and physical assistance based on care robotics for older adults (Stone et al., 2016). As a result, care robots can be regarded as one solution to the challenges the demographic change poses to the healthcare system.

Within our experiment, the general acceptance of care robots was high. The care robot was a popular choice in every round of the experiment, independent of the assigned treatment associated with the human caregiver. This is remarkable as one may typically assume that especially in a decision under the vail of ignorance, humans should be preferred. Moreover, we observe that quality issues affect the human decisions for their choice of care. However, the more likely a future need for care, the more likely is the human to choose a human care giver. As we refrained from sympathy and held quality equal, this is remarkable. If quality is equal, an unequal probability of being chosen can be regarded as discrimination. Our results thus reveal that we need to work on stereotypes against robots which may have prevented rational choice in our experiment. This in line with the strong relevance of attitudes in our experiment: Even though there was no real care situation, participants were in favor of human care depending on their prejudice. Participants with a higher negative attitude toward the characteristics of a robot in terms of their emotional components are significantly more likely to choose a human caregiver. Third, indecisive participants tend to choose a human caregiver significantly more often than decisive participants.

Our results show that even when there is no real care decision involved and even when the decision situation favors the robot in terms of risk neutrality – measured as the lower variance in outcomes – individuals prefer human care over robots. Thus, we need to think about the introduction of robots in the care sphere very carefully (Johansson-Pajala et al., 2020; Khaliq et al., 2018). Our experiment is a first hint into clear evidence on stereotypes as we show that individuals favor human care even in our very abstract situation. Other surveys and also experiments – especially field experiments with real robotic assistance (e.g. Papadopoulos et al., 2020, 2022)– may analyze how stereotypes and prejudice against robots can be mitigated, which will be needed in order to master the care crisis ahead.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. Introduction to the experiment given to the participants

You are in need of help for the next 10 days due to injury. You need help in all of your everyday chores from dressing up to eating and cleaning. You can either employ a human caregiver for 1 h a day or rent a robot for the whole time. Both options cost the same per day. Your satisfaction with both may vary.

Human caregiver:

- Works only 1 h per day. The person may vary.
- During that time s/he:
  - ○Gives you your medicine
  - ○Washes you
  - ○Offer you a meal

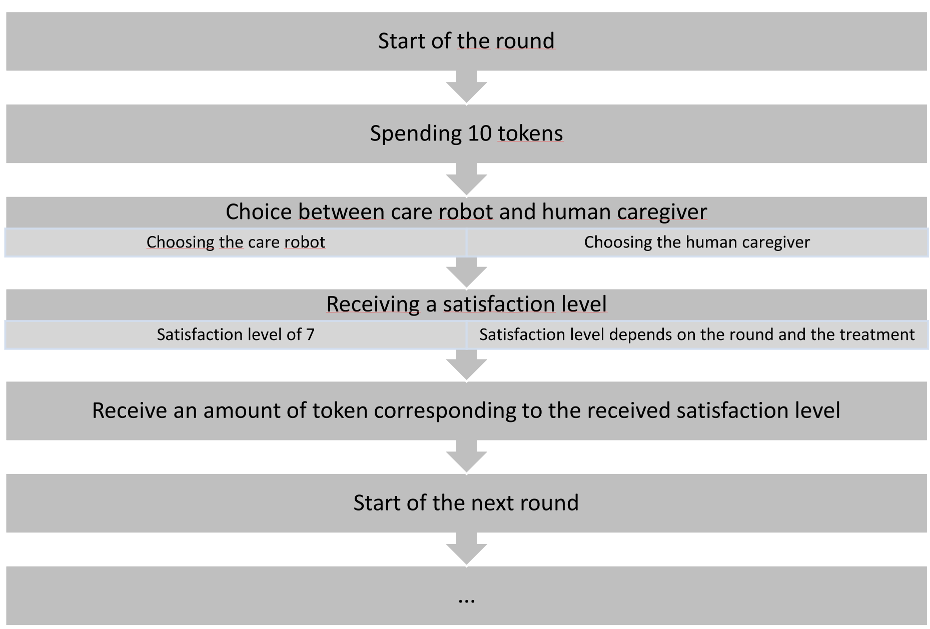
Robot:

- Is with you the whole day and the same robot is with you the whole time.
- During that time the robot:
  - ○Gives you your medicine
  - ○Washes you
  - ○Offers you a meal

You are endowed with 100 Token. Employing a human caregiver or a robot for one day costs 10 Token. Your satisfaction level ranges between 0 and 10 for a day. As the human care giver may vary from day to day, your satisfaction with her/his service may also vary from day to day. You may, for instance, like one person more than another or one person may provide a better service to you than another person. The robot will generate the same level of satisfaction for you each day.

For every level of satisfaction, the corresponding amount of tokens is added to your account. Your satisfaction is computed by taking into account your preferences and a randomly drawn service quality.

Appendix B. Procedure of the experiment



Appendix C: Technology Orientation Scale (Nomura et al., 2006)

Item No.	Question	Corresponding Factor
1	I would feel uneasy if robots really had emotions	S2
2	Something bad might happen if robots developed into living beings	S2
3	I would feel comfortable talking with a robot	Control variable to item 13
4	I would feel relaxed talking with robots	S3
5	I would feel uneasy if I was given a job where I had to use robots	S3
6	If robots had emotions, I would be able to make friends with them	S1
7	I feel comforted being with robots that have emotions	S1
8	The word "robot'' means nothing to me	S3
9	I would feel nervous operating a robot in front of other people	S3

(continued on next page)

(*continued*)

Item No.	Question	Corresponding Factor
10	I would hate the idea that robots or artificial intelligences were making judgments about things	S3
11	I would feel very nervous just standing in front of a robot	
12	I feel that if I depend on robots too much, something bad might happen	S2
13	I would feel paranoid talking with a robot	S3
14	I am concerned that robots would be a bad influence on children	S2
15	I feel that in the future society will be dominated by robots	S2

Note. S1: Negative attitude toward situations of interaction with robots, S2: Negative attitude toward social influence of robots, S3: Negative attitude toward emotions in interaction with robots.

Appendix D. Pairwise comparison of the different treatments regarding the choice for a robot (Wilcoxon-Mann-Whitney Test)

Treatments	z	p-Value	N
NSLV-PSLV	−0.855	.392	85
NSLV-NSHV	−0.318	.751	82
NSLV-PSHV	−1.303	.193	81
PSLV-NSHV	0.596	.551	81
PSLV-PSHV	−0.302	.763	80
NSHV-PSHV	−1.054	.292	77

Note. **NSLV:** Negative Start & Low-Quality Variance, **PSLV**: Positive Start & Low-Quality Variance, **PSHV**: Positive Start & High-Quality Variance, **NSHV**: Negative Start & High-Quality-Variance.

Appendix E. Correlation between the treatment and share of participants that choose a robot (in percent) for each round (chi-squared test):

Round	NSLV	PSLV	PSHV	NSHV
1	60.47	71.43	58.97	63.16
2	55.81	59.52	46.15	68.42
3	58.14	50.00	64.10	63.16
4	41.86**	69.05*	66.67	55.26
5	58.14	71.43	56.41	60.53
6	67.44	52.38	51.28	68.42
7	53.49	59.52	46.15	71.05*
8	46.51	54.76	61.54	60.53
9	44.19*	59.53	61.54	63.16
10	65.12	59.52	66.67	68.42

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The table shows the number of participants (in percent) that choose a robot in each round differentiated by their assigned treatment. A chi-squared test was used to test if there is a significant difference between the treatments in correlation to the probability of a participant choosing a robot.

Appendix F. Correlation between the treatment and share of participants that choose a robot (in percent) in each round (Fisher's exact test):

Round	NSLV	PSLV	PSHV	NSHV
1	60.47	71.43	58.97	63.16
2	55.81	59.52	46.15	68.42
3	58.14	50.00	64.10	63.16
4	41.86**	69.05	66.67	55.26
5	58.14	71.43	56.41	60.53
6	67.44	52.38	51.28	68.42
7	53.49	59.52	46.15	71.05*
8	46.51	54.76	61.54	60.53
9	44.19*	59.53	61.54	63.16
10	65.12	59.52	66.67	68.42

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix G. Correlation between the treatment and the decision for a robot in round 4, 7 and 9

Round/Treatment	Share of participants that choose a robot (in percent)	Pearson Chi	p-Value	Fisher's exact	N
Round 4					
NSLV	41.86	6.280	.012	.019	162
PSLV	69.05	2.829	.093	.105	162
NSHV	66.67	1.575	.209	.265	162
PSHV	55.26	0.155	.693	.711	162
Round 7					

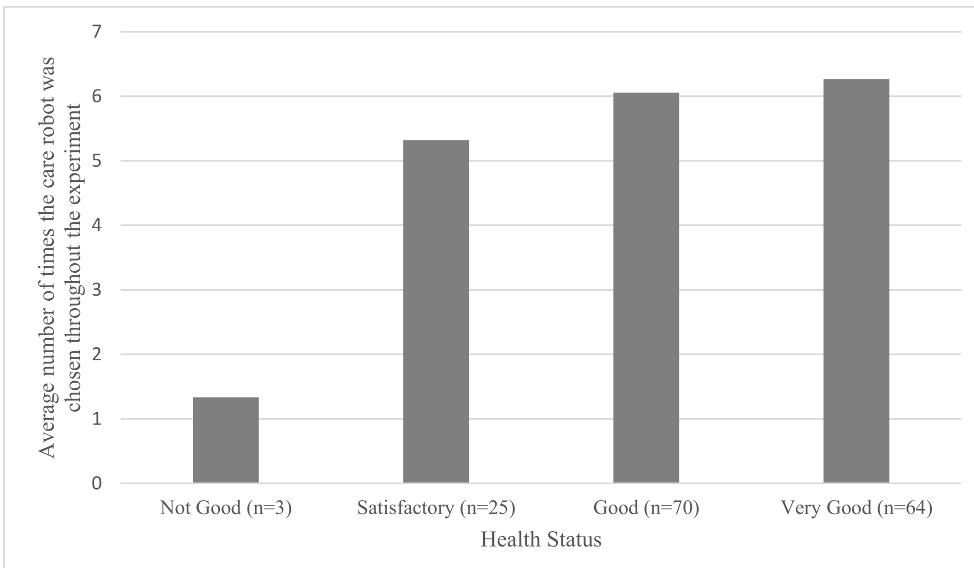
(*continued on next page*)

(*continued*)

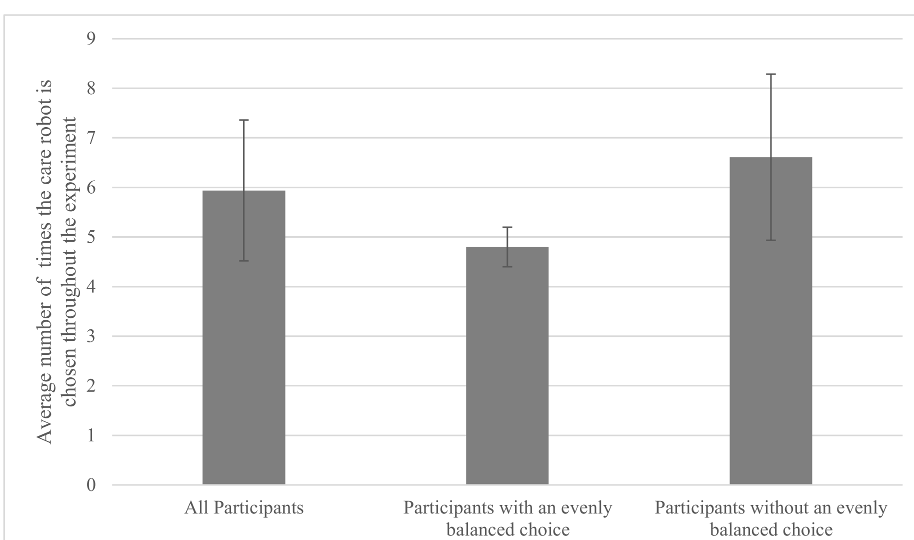
Round/Treatment	Share of participants that choose a robot (in percent)	Pearson Chi	p-Value	Fisher's exact	N
NSLV	53.49	0.368	.544	.592	162
PSLV	59.52	0.104	.747	.857	162
NSHV	46.15	2.660	.103	.137	162
PSHV	71.05	3.780	.052	.062	162
Round 9					
NSLV	44.19	3.790	.052	.072	162
PSLV	59.52	0.173	.678	.720	162
NSHV	61.54	0.472	.492	.579	162
PSHV	63.16	0.820	.365	.455	162

Note. **NSLV:** Negative Start & Low-Quality Variance, **PSLV**: Positive Start & Low-Quality Variance, **PSHV**: Positive Start & High-Quality Variance, **NSHV**: Negative Start & High-Quality-Variance.

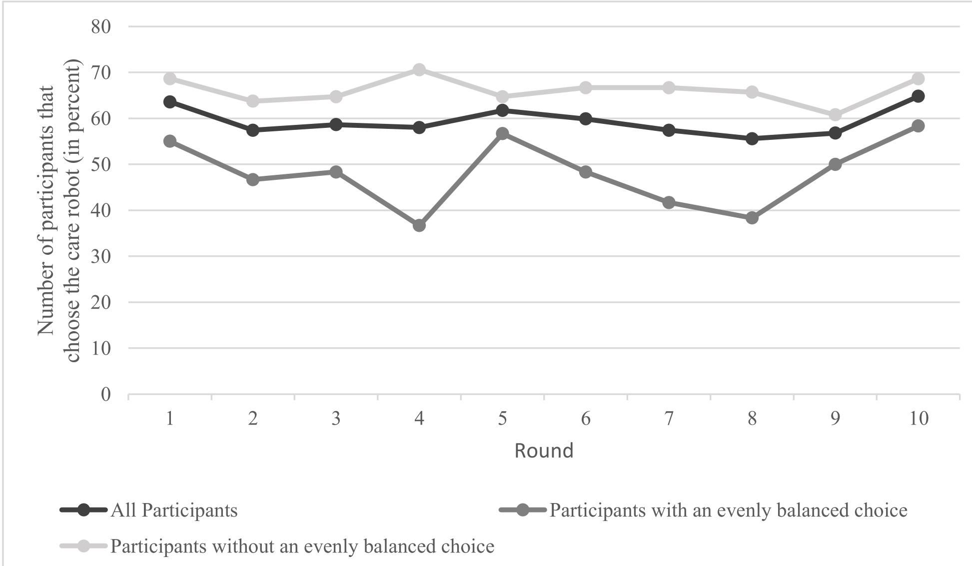
Appendix H. Health status of a participant and their choice between a human caregiver and a care robot



Appendix I. Choice for a robot throughout the experiment differentiated by participants having an evenly balanced choice or not



Appendix J. Choice for a robot in each round differentiated by participants having an evenly balanced choice or not



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