Latikka, R., Turja, T., & Oksanen, A. (2019) Self-Efficacy and Acceptance of Robots. *Computers in Human Behavior*, 93(April), 157–163. DOI: 10.1016/j.chb.2018.12.017.
<https://doi.org/10.1016/j.chb.2018.12.017>

Self-Efficacy and Acceptance of Robots

Abstract

As many post-industrial societies are rapidly ageing, intelligent and innovative solutions from the technology side are sought to ensure that welfare services continue in the future. Both social and nonsocial assistive robots are considered as solutions. To ensure the successful implementation of new technology, it is essential to understand the factors that influence the user's decision to accept or reject technology. The aim of this study was to understand the association between robot use self-efficacy and acceptance of robots. Acceptance of humanoid, pet, lifting, and telepresence robots were studied among care work staff ($N = 3800$). Analyses were based on linear regression analysis. The results showed that robot use self-efficacy is associated with the acceptance to use humanoid, pet, and telepresence robots. The strongest connection was found between robot use self-efficacy and the functional and social acceptance of a humanoid robot. General self-efficacy was not associated with any of the robot types studied in the final models. Furthermore, no interaction effect was found between general self-efficacy and robot use self-efficacy. The results underline that psychological processes on acceptance of robots vary between different types of robots. The results imply that robot use self-efficacy is important for understanding acceptance and implementation of robots. The explanatory power of self-efficacy is better when it is tied to a specific matter such as the use of care robots.

Keywords: self-efficacy, robot use self-efficacy, robots, technology, user acceptance, user experience

Self-Efficacy and Acceptance of Robots

As many post-industrial societies are rapidly ageing, fresh and innovative solutions from the technology side are sought to ensure that welfare services continue in the future. A partial solution to support the quality of welfare services is proposed to be found in robots (Broadbent, Stafford, & MacDonald, 2009; Koceski & Koceska, 2016). The advances in artificial intelligence enable robots to act more autonomously and thus re-arrange care work (Broekens, Heerink, & Rosendal, 2009; Van Wylsberghe, 2013).

In this study, *service robot* stands for a professional or non-professional device that is programmable for at least two axes and is capable of moving around in the environment to carry out useful tasks for the human or is not within the industry. Its degree of autonomy may vary from human-driven partial autonomy to fully automated robots (ISO 8373: 2012), and it is seen as a combination of both hardware and software robotics. Robots in welfare services can be categorized into social and nonsocial assistive robots (Heerink, Kröse, Evers, & Wielinga, 2010) as the robot prefix “social” stands for a robot’s ability to recognize other robots and humans and communicate with, learn from, and engage in social interaction with them (Fong, Nourbakhsh, & Dautenhahn, 2003). In this study, a telepresence robot is also categorized as a social robot, since it involves human presence.

For the home-care customers, care robots are believed to be useful, for example by (a) assisting home care customers and their caregivers in daily tasks, (b) monitoring behavior and health, and (c) providing companionship (Sharkey & Sharkey, 2010) as well as facilitating social interaction (Koceski & Koceska, 2016) and acting as a therapeutic tool (Shibata, 2012). For example, the humanoid robot Zora (Johnson, Cuijpers, Pollmann, & van de Ven, 2016; Melkas, Hennala, Pekkarinen, & Kyrki, 2016), the telepresence robot Double (Koceski & Koceska, 2016; Schulman et al., 2013), and the therapeutic pet robot Paro (Shibata, 2012; Wada & Shibata, 2004) are robots developed for these purposes. Besides, for example in surgery, robotics has been utilized for a long time (Palep, 2009; Wasen, 2010). Also, care workers have considered the robots in elder care to be useful, especially in lifting heavy loads (Broadbent et al., 2012).

The care worker’s viewpoint in the acceptance of new technology is particularly important, as they work closest to the home care customers and thus affect their ability and direct quality of care (From, Nordström, Wilde-Larsson, & Johansson, 2013). To ensure the successful implementation of new technology, it is essential to understand the factors that influence the user’s decision to accept or reject technology (Hasan, 2006; Venkatesh, 2000). Self-efficacy is one of the key drivers of human activity (Bandura 2006), and it has been found to have both direct and indirect impact on the intention and actual use of different technologies (e.g., Agarwal, Sambamurthy, & Stair, 2000; Hasan, 2006; Hsu & Chiu, 2004; Rahman, Ko, Warren, & Carpenter, 2016).

The aim of this study was to analyze the association between robot use self-efficacy and acceptance of assistive robots. Theoretically this study is based on Bandura’s theory of self-efficacy. Acceptance of both social and nonsocial assistive robots were studied with users having firsthand user experience of assistive robots toward both social and nonsocial robots. Acceptance of robotics is in this study defined as a positive user experience of robots.

Self-efficacy and Usage of Technology

According to the widely used Bandura’s (1977, 1986, 1997) theory of self-efficacy, *self-efficacy* refers to an individual’s estimates or beliefs about his/her own ability to perform in a particular situation or task. Instead of actual abilities, the individual’s estimates of what he/she can do with his/her own skills are essential. Self-efficacy is one of the guiding factors of human activity: It affects human behavior both directly and via its effects, such as the individual’s

motivation, thinking patterns, and, for example, how much and how long an individual strives to accomplish a particular situation or task (Bandura, 2006). However, it has also been stated (Williams & Rhodes, 2014) that people's views of their abilities reflect a broader concept of motivation rather than solely self-efficacy, which somewhat problematizes the connection between motivation and self-efficacy. As self-efficacy consists of perceptual beliefs related to the specific activity of an individual, its measurement must be tied up with a particular situation and task (Bandura, 2006; Bong, 2006).

In the technology context, self-efficacy has been explored within the use of computers (e.g., Compeau & Higgins, 1995; Marakas, Yi, & Johnson, 1998), software (Agarwal et al., 2000; Hasan, 2006) and the Internet (Eastin & LaRose, 2000; Hsu & Chiu, 2004), after which time, self-efficacy research has also extended to the context of health technology (Rahman et al., 2016) and robotics (Turja, Rantanen, & Oksanen, 2017). Computer self-efficacy refers to the ability of the individual to use a computer, and individuals with high computer self-efficacy used more computers, enjoyed their use, and experienced less anxiety about using them (Compeau & Higgins, 1995). Computer self-efficacy has also been divided into general computer self-efficacy (GCSE) and task-specific computer self-efficacy (CSE), and task-specific computer self-efficacy has been further divided into application environments and specific applications sub-levels (Marakas et al., 1998). In the software context, general computer self-efficacy has been found to have a significant impact on software specific self-efficacy, particularly in the early stages of training, and previous experience was found to have a significant effect on general computer self-efficacy but not on software-specific self-efficacy (Agarwal et al., 2000).

Internet self-efficacy (ISE; e.g., Eastin & LaRose, 2000) has also been divided into general internet self-efficacy (GISE) and web-specific self-efficacy (WSE; Hsu & Chiu, 2004). General Internet self-efficacy has been found to positively predict the web-specific self-efficacy of an individual; web-specific self-efficacy had a significant direct impact on the use of online services, while general internet self-efficacy had an indirect effect on the use of online services through web-specific self-efficacy, attitude, and behavioral intention (Hsu & Chiu, 2004). Similarly, in a related software application study, general computer self-efficacy predicted system-specific self-efficacy, and system-specific self-efficacy predicted intention to use technology, whereas general computer self-efficacy predicted intention to use technology only through system-specific self-efficacy and ease of use of technology (Hasan, 2006).

Health technology self-efficacy (HTSE) indicates individuals' perceptions of their ability to use health technologies such as devices used to diagnose, monitor, or treat health or any individual's health condition (Rahman et al., 2016). In the context of software (Agarwal et al., 2000), Internet (Hsu & Chiu, 2004), and software applications (Hasan, 2006), a positive relation between the general technology context-related self-efficacy and the task-specific self-efficacy was found. Similarly, both general self-efficacy and general computer self-efficacy were found to predict health technology self-efficacy, and health technology self-efficacy had a positive influence on attitude toward the use of health technologies (Rahman et al., 2016). Robot use self-efficacy (RUSH) refers to the beliefs of care workers about their ability to use robots, and it has been found to be a separate construct from general self-efficacy (Turja et al., 2017).

Acceptance and Implementation of Robots

Organizations invest in new information technology in order to maintain and improve their competitiveness, but technology investments do not yet guarantee that people will use new equipment or systems (Beedholm, Frederiksen, Skovsgaard Frederiksen, & Lomborg, 2015; McFarland & Hamilton, 2006). Self-efficacy has been shown to have a direct impact on the intent of using different technologies in the context of healthcare (Ma & Liu, 2005), online

shopping (Vijayasathy, 2004), teaching (Hu, Clark, & Ma, 2003), and computer usage (Teo, 2009). Self-efficacy has also been found to have direct effects on the actual use of technology (Yi & Hwang, 2003). However, the connection between self-efficacy and user experience is not unambiguous, as some studies have not found self-efficacy to have direct effect on intention to use technology (e.g., Heerink et al., 2010; Venkatesh, Morris, Davis, & Davis, 2003). Self-efficacy has also been found to influence technology acceptance indirectly on different factors related to user experience such as attitudes (Hsu & Chiu, 2004), anxiety (Compeau & Higgins, 1995; Czaja et al., 2006), ease of use (Hasan, 2006; Hu et al., 2003; Igabria & Iivari, 1995; Venkatesh, 2000), and usefulness (Teo, 2009).

Previous technology experience and interest in technology are also known to predict technology acceptance (Heerink, 2011; Nomura, Kanda, & Suzuki, 2006). Previous experience also positively influences self-efficacy (Igbaria & Iivari, 1995), and high self-efficacy predicts a broader prior experience (Hu et al., 2003). As the prior experience increases, however, the net effect of self-efficacy in technology acceptance falls (Hu et al., 2003). New technologies are typically accepted by young people more than older people, men more than women, and the highly educated more than the less educated (de Graaf & Ben Allouch, 2013; Heerink, 2011; Flandorfer, 2012; Scopelliti, Giuliani, & Fornara, 2005). However, previous experience with technology has been found to mitigate the influence of sociodemographic factors (e.g. age and gender) on acceptance: When technology becomes more familiar to its users, it is likely that the effects of sociodemographic factors will decrease. (Flandorfer, 2012.)

The acceptance of robots has much in common with the acceptance of other technologies, but it has some unique characteristics as well. Although robots have been in the industry for years, most of the research in robot acceptance has examined service robotics (Savela, Turja, & Oksanen, 2017). Their possible benefits in welfare services (Koceski & Koceska, 2016; Sharkey & Sharkey, 2010; Shibata et al., 2012) are also of interest because welfare services have been considered to be a human-centered field (Nourbakhsh, 2015). In addition to user and technology review, taking into account a certain professional context is central to understanding new technology acceptance (Chau & Hu, 2002; Hu et al., 2003). The attitudes toward robots in various professional tasks has been studied most precisely in the social and health sectors (Savela et al., 2017).

Care workers have been more concerned about care robots than elderly people and their relatives, which has been interpreted as originating from fear of losing their jobs (Broadbent et al., 2012), seeing technology as competing with human contact (Saborowski & Kollak, 2015), suspicion of whether nursing robots are useful in elderly care (Wolbring & Yumakolov, 2014), or difficulties in evaluating them resulting from lack of prior experience (Fuji et al., 2011). However, care workers see robots as most useful in lifting heavy things, turning on and switching lights off, closing and launching electronic devices, access control work (Broadbent et al., 2012), monitoring vital signs, facilitating social communication, and providing medication reminders (Alaiad & Zhou, 2014). Care workers have also been shown to be adopting, for example, a bath robot (Beedholm et al., 2015), working together with a robot surgeon (Wasen, 2010), monitoring robots (Jenkins & Draper, 2015), and telepresence robots (Koceski & Koceska, 2016).

Due to the fact that service robotics is an emerging field there is currently lack of studies investigating difference between acceptance of social and nonsocial robots. It is however possible that robot types that are closer to traditional machines already used in industrial automation for decades are easier to be accept (Taipale, Luca, Sarrica, & Fortunati, 2015). Previous studies have for example noted that people find human-like robots more uneasy than mechanical robots (Arras & Cerqui, 2005; Gray & Wegner, 2012; Kätsyri, Förger, Mäkäraäinen, & Takala, 2015). Also, robots are less readily accepted in work fields relying on human interaction, such as care work (Savela, et al., 2018). For these reasons perhaps, there are also differences on the relationship between self-efficacy and acceptance of social and nonsocial robots.

Hypotheses

This article reports findings in research conducted among care work staff. Our aim was to study the relationship between robot use self-efficacy and acceptance of both social and nonsocial assistive robots. We examined the relationship between robot use self-efficacy and acceptance of assistive robots as well as the changes that occur when other background variables selected in a research set are considered in the review. In addition, by including both robot use self-efficacy and general self-efficacy in the research setup, our aim was to examine self-efficacy and acceptance of new technology in a broader sense.

Our hypotheses are based on previous literature on different technological forms of self-efficacy (Agarwal et al., 2000; Hasan, 2006; Hsu & Chiu, 2004; Rahman et al., 2016) and the theory of self-efficacy (Bandura 1997, 1986, 1997, 2006). Our study provides new evidence on social and nonsocial assistive robots, which have not been previously studied in relation to the self-efficacy. We hypothesized:

- H1. Robot use self-efficacy directly predicts acceptance of assistive robots
- H2. General self-efficacy does not directly predict acceptance of assistive robots
- H3. General self-efficacy predicts robot use self-efficacy

Method

Participants

This study was conducted among care work staff in Finland. A representative sample of care work staff was collected via two major unions in October–November 2016: The Finnish Union of Practical Nurses and the Union of Health and Social Care Professionals in Finland. The respondents for both surveys were drawn from the union member registers and contacted via email. Voluntary participants then filled the survey online. The survey was administrated with Limesurvey software run in the University server.

The first survey yielded a total response rate of 11.0%, and the second survey yielded a 9.0% response rate. In total, 3800 people responded to the surveys, but the analyses focus on those respondents who have had firsthand experience of assistive robots ($n = 501$). The participants were mostly female (94.6%) and were aged 17–70 ($M = 46.50$; $SD = 11.30$).

Measures

Acceptance of robots. This study included four different dependent variables. Each of the variables considered care workers' experience of different robot type separately. Investigation involved acceptance of both social robots (humanoid, pet, and telepresence robots) and non-social robots (lifting robot). Each of these robot types had a set of nine question measures that was applied from Heerink's questions of functional and social acceptance (Heerink et al., 2010). Therefore, in this study user acceptance was studied via user experience which is a collection of nine different variables applied from Heerink's study. All nine variables predict intention to use technology and the actual use of technology and they hence refer to positive user experience. For example, a question of perceived usefulness was formed as "I think the [robot] would be useful in my job" (See Appendix A for the English translations of all the nine statement questions).

All dependent measures showed good inter-item consistency: Humanoid robots ($\alpha = .75$), pet robots ($\alpha = .83$), telepresence robots ($\alpha = .79$), and lifting robots ($\alpha = .79$), and as a composite variable, the measure had excellent reliability ($\alpha = .94$). Questions of the dependent

variables were shown only for participants with experience of the robot in question. Less than 10 percent of the participants had experience of some of these robots, which also affected the number of participants and thus the final sample size.

Robot use self-efficacy. The main interest in analysis relies on the relation of robot use self-efficacy and acceptance of four different robots. This study used a validated robot use self-efficacy in health work (RUSH-3) scale (Turja et al., 2017). It involved three questions: (a) I'm confident in my ability to learn how to use care robots if they were to become part of my unit, (b) I'm confident in my ability to learn simple programming of care robots if I were provided the necessary training, and (c) I'm confident in my ability to learn how to use care robots in order to guide others to do the same. This three-question measure had good reliability ($\alpha = .84$). See Table 1 for exact details.

Socio-demographic background variables. Age ($M = 46.50$, $SD = 11.30$, range 17–70) and gender (94.6% female) were used as controls in the models.

Technology variables. Robot experience was asked with a question: "Which of the following devices that are called as a care robot will be familiar to you through practical work?" The care robots were: (a) telepresence robots (or mobile video callers), (b) humanoid robots (e.g., Zora), (c) pet robots (e.g., Paro), and (d) robots designed for lifting or moving human beings. The composite variable formed a 0–4 scale ($M = 0.19$, $SD = 0.49$). The robot types were the same as in the dependent variables. Interest of technology was asked with a question modified from Special Eurobarometer 382 (2012): "Are you very interested (3), moderately interested (2), or not at all interested (1) in technology and its developments?" ($M = 2.07$, $SD = 0.49$).

General self-efficacy. General efficacy was measured with the short form general efficacy scale (GSE-6; Rompel et al., 2013). It involved six questions: (a) If someone opposes me, I can find means and ways to get what I want; (b) it is easy for me to stick to my aims and accomplish my goals; (c) I am confident that I could deal efficiently with unexpected events; (d) thanks to my resourcefulness, I know how to handle unforeseen situations; (e) I can remain calm when facing difficulties because I can rely on my coping abilities; and (f) no matter what comes my way, I'm usually able to handle it. This six-question measure had high reliability ($\alpha = .81$). See Table 1 for exact details.

Statistical Analyses

The analysis involved both descriptive statistics and ordinary least squares (OLS) regression models. The models were run separately for each robot type. Model 1 included only robot use self-efficacy, model 2 adjusted for gender and age, model 3 added robot experience and interest in technology and its development, and finally in model 4 general self-efficacy was added. All variables were introduced to the model in a specific order for enabling the examination of changes that occur when other background variables are considered in the review and to control the research model. All of the models were additionally tested for potential problems with multicollinearity and heteroscedasticity of residuals. We reported non-standardized (B) and standardized (β) regression coefficients, standard errors, and p-values for statistical significance. A separate test on the interaction effect between self-efficacy variables was also conducted and reported.

Results

Table 1 shows descriptive statistics for the variables. The participants were mostly female (94.6%), and the average age was 46.50 years. The most well-known robot type among participants was the pet robot ($n = 220$), and the second-most well-known type was the humanoid robot ($n = 104$). Participants showed relatively high robot use self-efficacy ($M =$

4.19, $SD = 0.77$) and interest in technology and its development ($M = 2.07$, $SD = 0.49$) but low general self-efficacy ($M = 2.63$, $SD = 0.91$) and robot experience ($M = 0.19$, $SD = 0.49$). Furthermore, within correlation analysis, no significant correlation was found between general self-efficacy and robot use self-efficacy.

Table 2 shows the results of linear regression between robot use self-efficacy and acceptance of humanoid robots. In Model 1, the results indicated that robot use self-efficacy significantly predicted acceptance of humanoid robots ($\beta = .53$, $p < .001$). In the third model, interest in technology and its development was found to predict acceptance of humanoid robots ($\beta = .18$, $p < .05$). In the last model, the connection between robot use self-efficacy and acceptance of humanoid robots moderately decreases but remains significant ($\beta = .48$, $p < .001$). Together, the variables explained 31% of the variance ($R^2 = .31$, $F = 8.60$, $p < .001$).

Table 3 shows the results of linear regression between robot use self-efficacy and acceptance of pet robot. In Model 1, the results indicated that robot use self-efficacy significantly predicted acceptance of pet robots ($\beta = .33$, $p < .001$). In the second model, the male gender was found to negatively predict acceptance of humanoid robots ($\beta = -.15$, $p < .05$). In the last model, the connection between robot use self-efficacy and acceptance of pet robots moderately strengthens and remains significant ($\beta = .34$, $p < .001$). Together, the variables explain 12% of the variance ($R^2 = .12$, $F = 6.01$, $p < .001$).

Table 4 shows the results of linear regression between robot use self-efficacy and acceptance of lifting robots. In Model 1, the results indicated that robot use self-efficacy did not significantly predict acceptance of lifting robots. In other models, none of the variables predicted acceptance of lifting robots, either. Hence, this model was not able to explain the connection in question.

Table 5 shows the results of linear regression between robot use self-efficacy and acceptance of telepresence robots. In Model 1, the results indicated that robot use self-efficacy significantly predicted acceptance of telepresence robots ($\beta = .44$, $p < .001$). In the third model, robot experience ($\beta = .20$, $p < .05$) and interest in technology and its development ($\beta = .33$, $p < .01$) were found to predict acceptance of telepresence robots. In the last model, the connection between robot use self-efficacy and acceptance of telepresence robots decreases but still remains significant ($\beta = .27$, $p < .001$). Together, the variables explain 30% of the variance ($R^2 = .30$, $F = 6.84$, $p < .001$).

In all of the models, neither age nor general self-efficacy predicted any of the robot types studied. No interaction effect was found between robot use self-efficacy and general self-efficacy, either ($p > 0.05$).

Discussion

This was the first study analyzing the association between robot use self-efficacy and acceptance of social and non-social assistive robots. Acceptance of robots was defined in this study as positive user experience that is related to both intention to use and actual use of robots. Our results showed that robot use self-efficacy was associated with acceptance of humanoid, pet, and telepresence social robots but not with lifting nonsocial robot. General self-efficacy was not associated with any of the four robot types. Additionally, no interaction effect was found between general self-efficacy and robot use self-efficacy.

The results partially confirm the first hypothesis of the study: Robot use self-efficacy predicts the functional and social acceptance of humanoid, pet, and telepresence robots. The findings are in line with previous literature concerning task-specific self-efficacy and attitude toward the use of technology (Rahman et al., 2016), intention to use technology (Hasan, 2006), as well as the actual use of technology (Hsu & Chiu, 2004). Further, our results indicate that task-specific self-efficacy predicts different user experience related factors, such as attitudes (Hsu & Chiu, 2004), anxiety (Compeau & Higgins, 1995; Czaja et al., 2006), ease of use

(Hasan, 2006; Hu et al., 2003; Igabria & Iivari, 1995; Venkatesh, 2000), and usefulness (Teo, 2009) which have previously studied within technology context related self-efficacy.

However, our study provided new evidence on robot use self-efficacy and user experience of assistive robots. That is, robot use self-efficacy is associated with acceptance of the assistive social robots studied but not with nonsocial robots. Among assistive social robots, the strongest connection was found between robot use self-efficacy and the functional and social acceptance of a humanoid robot. This finding seems interesting, as the appearance of humanoid robots are the most human-like among the robots studied. This perspective also provides new empirical understanding on acceptance of assistive robots. It partly fits also to the perspective where human-likeness of robots have been investigated (Arras & Cerqui, 2005; Gray & Wegner, 2012; Kätsyri, Förger, Mäkräinen, Takala, 2015). Our results at least underline that the role of robot use self-efficacy becomes stronger as the social and human aspects of robots increase. One potential explanation could be that human-likeness in robots' shape may indicate the kind of tasks a robot is able to do and thus, people feel more confident about handling and learning those skills eventually. Another way of looking at it is that robot use self-efficacy is not part of the acceptance phenomenon if the robot strongly resembles a machine. This finding might have practical importance when designing and implementing assistive robots.

General self-efficacy was not associated with any of the four robot types. The results confirm our second hypothesis: General self-efficacy does not directly predict acceptance of assistive robots (Hasan, 2006; Hsu & Chiu, 2004; Rahman et al., 2016). Therefore, general self-efficacy was associated with neither assistive social robots nor non-social robots. However, it is also noteworthy that in previous research, there are mixed findings on the relationship between self-efficacy and technology usage behavior, as some studies have not found self-efficacy to have direct effect on intention to use technology (e.g., Heerink, 2010; Venkatesh et al., 2003).

The results do not confirm our third hypothesis on association between general self-efficacy and robot use self-efficacy. Furthermore, no interaction effect was found between general self-efficacy and robot use self-efficacy, and hence our study cannot fully confirm the effecting connection between these two variables. Overall, our findings underline the relevance of task-specific self-efficacy when researching acceptance of robots. The results show that the explanatory power of self-efficacy is better when it is tied to a specific matter such as the use of care robots (Bandura 2006). The benefits of task-specificity also include better measurement accuracy, as the respondents know what they are assessing in their own ability (Bong 2006).

The development of robots has been rapid recently, but different technologies have been in use for a long time. Therefore, it can be assumed that technology-related self-efficacy has evolved as different technologies have been introduced and adopted. For these reasons we theoretically assumed that robot use self-efficacy has developed first before the acceptance of robot technology. The relation between robot use self-efficacy and other forms of technological self-efficacy should be studied in future. This could give us important contextual knowledge on usage of technology and robots in general.

Limitations

As a potential limitation, it is crucial to consider whether the results of general self-efficacy research can be paralleled with the general self-efficacy in technology context findings. Besides, interpreting self-efficacy measurements can also be challenging, as people may interpret self-efficacy assessments differently. In practice, we have limited possibilities to conclude whether the self-efficacy measurements are interpreted as assessments of one's own ability (Bandura 1977, 1986, 1997, 2006) or motivation in a broader sense (Williams & Rhodes, 2014). On the other hand, as the data was limited to care workers in Finland, one

country offers a unified language region, which may reduce the possible conflict in concept interpretation. Our study was also limited by a cross-sectional research design and hence it is impossible to estimate the development of technological self-efficacy over time. Longitudinal studies noting how technological self-efficacy changes after the of new technologies would be important to conduct in the future.

Conclusion

Robot use self-efficacy predicted acceptance of humanoid, pet, and telepresence robots (assistive social robots), whereas general self-efficacy did not have an effect on any of the robot types studied. The results imply that the explanatory power of self-efficacy is better when it is tied to a technology-specific matter such as the use of care robots. Among assistive social robots, robot use self-efficacy had the strongest connection to the functional and social acceptance of humanoid robots. Our results underline that the role of robot use self-efficacy becomes stronger as the social and human aspects of robots increase. Future studies should continue investigating the functional and social acceptance of humanoid robots. These findings offer new insights for practitioners, professionals, and future research in acceptance and implementation of assistive robots.

References

- Agarwal, R., Sambamurthy, V., & Stair, R. M. (2000). Research report: The evolving relationship between general and specific computer self-efficacy—An empirical assessment. *Information Systems Research*, 11(4), 418–430.
- Arras, K.O., & Cerqui, D., (2005). *Do we want to share our lives and bodies with robots? A 2000 people survey*. Technical Report Nr. 0605-001. Lausanne: Autonomous Systems Lab, Swiss Federal Institute of Technology Lausanne (EPFL).
- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84, 191–215.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. New Jersey: Prentice-Hall.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: Freeman.
- Bandura, A. (2006). Guide for creating self-efficacy scales. In F. Pajares & T. Urdan (Eds.), *Self-efficacy beliefs of adolescents*, 307–337. Greenwich: Information Age Publishing.
- Beedholm, K., Frederiksen, K., Skovsgaard Frederiksen, A.M., & Lomborg, K. (2015). Attitudes to a robot bathtub in Danish elder care: A hermeneutic interview study. *Nursing and Health Sciences*, 17(3), 280–286.
- Bong, M. (2006). Asking the right question. How confident are you that you could successfully perform these tasks? In F. Pajares & T. Urdan, (Eds.), *Self-efficacy beliefs in adolescents*, 287–305. Greenwich: Information Age Publishing.
- Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. *International Journal of Social Robotics*, 1(4), 319–330.
- Broadbent, E., Tamagawa, R., Patience, A., Knock, B., Kerse, N., Day, K., & MacDonald, B. A. (2012). Attitudes towards health-care robots in a retirement village. *Australasian Journal of Ageing*, 31(2), 115–120.
- Broekens, J., Heerink, M., & Rosendal, H. (2009) Assistive social robots in elderly care: A review. *Gerontechnology*, 8(2): 94–103. <https://doi.org/10.4017/gt.2009.08.02.002.00>
- Chau, P.Y.K., & Hu, P.J.-H. (2002). Investigating healthcare professionals' decisions to accept telemedicine technology: An empirical test of competing theories. *Information & Management*, 39, 297–311.
- Compeau, D. R., & Higgins, C. A. (1995). Application of social cognitive theory to training for computer skills. *Information Systems Research*, 6, 118–143.
- Czaja, S. J., Charness, N., Fisk, A., Hertzog, C., Nair, S., Rogers, W., & Sharit, J. (2006). Factors predicting the use of technology: Findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and Aging*, 21 (2), 333–352.
- De Graaf, M. M. A., & Ben Allouch, S. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems*, 61, 1476–1486.
- Eastin, M. S., & LaRose, R. (2000). Internet self-efficacy and the psychology of the digital divide. *Journal of Computer-Mediated Communication*, 6 (1).
- Flandorfer, P. (2012). Population ageing and socially assistive robots for elderly persons: The importance of sociodemographic factors for user acceptance. *International Journal of Population Research*.
- Fong, T., Nourbakhsh, I., & Dautenhahn, K. (2003). A survey of socially interactive robots. *Robotics and Autonomous Systems*, 42(3), 143–166.
- From, I., Nordström, G., Wilde-Larsson, B., & Johansson, I. (2013). Caregivers in older peoples' care: Perception of quality of care, working conditions, competence and personal health. *Scandinavian Journal of Caring Sciences*, 27(3), 704–714.
- Fuji, S., Date, M., Nagai, Y., Yasuhara, Y., Tanioka, T., & Ren, F. (2011). Research on the possibility of humanoid robots to assist in medical activities in nursing homes and

- convalescent wards. *7th International Conference on Natural Language Processing and Knowledge Engineering*, 459–463.
- Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition*, 125(1), 125–130.
- Hasan, B. (2006). Delineating the effects of general and system-specific computer self-efficacy beliefs on IS acceptance. *Information & Management*, 43(5), 565–571.
- Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010). Assessing acceptance of assistive social agent technology by older adults: The Almere Model. *International Journal of Social Robotics*, 2(4), 361–375.
- Heerink, M. (2011). Exploring the influence of age, gender, education and computer experience on robot acceptance by older adults. *Proceedings of the 6th international conference on Human-robot interaction*. Lausanne, Switzerland.
- Hu, P. J.-H., Clark, T. H. K., & Ma, W. W. (2003). Examining technology acceptance by school teachers: A longitudinal study. *Information & Management*, 41, 227–241.
- Hsu, M.-H., & Chiu, C.-M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems*, 38(3), 369–381.
- Igbaria, M., & Iivari, J. (1995). The effects of self-efficacy on computer usage. *OMEGA International Journal of Management Science*, 23(6), 587–605.
- International Organization for Standardization. (2012). Robots and robotic devices (ISO 8373:2012). Retrieved from <https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en>
- Jenkins, S., & Draper, H. (2015). Care, monitoring, and companionship: Views on care robots from older people and their carers. *International Journal of Social Robotics*, 7(5), 673–683.
- Johnson, D.O., Cuijpers, R.H., Pollmann, K., & van de Ven, A.A.J. (2016). Exploring the entertainment value of playing games with a humanoid robot. *International Journal of Social Robotics*, 8(2), 247–269
- Koceski, S., & Koceska, N. (2016). Evaluation of an assistive telepresence robot for elderly healthcare. *Journal of Medical Systems*, 40(5), 121.
- Kätsyri, J., Förger, K., Mäkäriäinen, M., & Takala, T. (2015). A review of empirical evidence on different uncanny valley hypotheses: Support for perceptual mismatch as one road to the valley of eeriness. *Frontiers in Psychology*, 6, 390. <http://dx.doi.org/10.3389/fpsyg.2015.00390>
- Ma, Q., & Liu, L. (2005) The role of internet self-efficacy in the acceptance of web-based electronic medical records. *Journal of Organization and End User Computing*, 17(1), 38–57.
- Marakas, G. M., Yi, M. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research* 9(2), 126–163.
- McFarland, D., & Hamilton, D. (2006). Adding contextual specificity to the technology acceptance model. *Computer in Human Behavior*, 22(3), 427–447.
- Melkas, H., Hennala, L., Pekkarinen, S., & Kyrki, V. (2016), Human impact assessment of robot implementation in Finnish elderly care. *4th International Conference on Serviceology*, Tokyo, Japan, p. 202–206. Available at: http://roseproject.aalto.fi/images/publications/ICServe_Melkas.pdf
- Nomura, T., Kanda, T., & Suzuki, T. (2006). Experimental investigation into influence of negative attitudes toward robots on human–robot interaction. *AI & Society*, 20(2), 138–150.
- Nourbakhsh, I. R. (2015). The coming robot dystopia. *Foreign Affairs* 94(4).
- Rahman, M. S., Ko, M., Warren, J., & Carpenter, D. (2016), Healthcare technology self-efficacy (HTSE) and its influence on individual attitude: An empirical study. *Computers in Human Behavior*, 58, 12–24.

- Romppel, M., Herrmann-Lingen, C., Wachter, R., Edelmann, F., Düngen, H-D, Pieske, B., & Grande, G. (2013). A short form of the General Self-Efficacy Scale (GSE-6): Development, psychometric properties and validity in an intercultural non-clinical sample and a sample of patients at risk for heart failure. *Psycho-Social Medicine*, 10.
- Saborowski, M. Kollak, I. (2015). "How do you care for technology?"—Care professionals' experiences with assistive technology in care of the elderly. *Technological Forecasting & Social Change*, 93, 133–140.
- Savela, N., Turja, T., & Oksanen, A. (2017). Social acceptance of robots in different occupational fields: A systematic review. *International Journal of Social Robotics*, 1–10. doi: 10.1007/s12369-017-0452-5.
- Schulman, C. I., Marttos, A., Graygo, J., Rothenberg, P., Alonso, G., Gibson, S., . . . Kelly, E. (2013) Usability of telepresence in a level 1 trauma center. *Telemedicine and e-Health* 19(4), 248–251.
- Scopelliti, M., Giuliani, M. V., & Fornara, F. (2005). Robots in a domestic setting: A psychological approach. *Universal Access in the Information Society*, 4(2), 146–155.
- Sharkey, A., & Sharkey, N. (2010). Granny and the robot: Ethical issues in robot care for the elderly. *Ethics and Information Technology* 14(1), 27–40.
- Shibata, T. (2012). Therapeutic seal robot as biofeedback medical device: Qualitative and quantitative evaluations of robot therapy in dementia care. *Proceedings of IEEE*, 100 (8), 2527–2538.
- Special Eurobarometer 382 (2012). Public attitudes towards robots. European Commission.
- Taipale, S., Luca, F.D., Sarrica, M., Fortunati, L. (2015). Robot shift from industrial production to social reproduction. In: Vincent, J., Taipale, S., Sapio, B., Lugano, G., Fortunati, L. (eds), *Social robots from a human perspective*. Springer, Switzerland, 11-24.
- Teo, T. (2009). Modelling technology acceptance in education: A study of pre-service teachers. *Computers & Education*, 52, 302–312.
- Turja, T., Rantanen, T., & Oksanen, A. (2017). Robot use self-efficacy in healthcare work (RUSH): Development and validation of a new measure. *AI & Society*, <https://doi.org/10.1007/s00146-017-0751-2>
- Van Wynsberghe, A. (2013). Designing robots for care: Care centered value-sensitive design. *Science and Engineering Ethics*, 19(2), 407–433.
- Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research* 11(4), 342–365.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
- Vijayasarathy, L.R. (2004). Predicting consumer intentions to use online shopping: The case for an augmented technology acceptance model. *Information and Management* 41(6), 747–762.
- Wada, K., & Shibata, T. (2008). Social and physiological influences of living with seal robots in an elderly care house for two months. *Gerontechnology*, 235. 7(2):235-235
- Wolbring, G., & Yumakulov, S. (2014). Social robots: Views of staff of a disability service organization. *International Journal of Social Robotics*, 6(3), 457–468.
- Yi, M.Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies* 59(4), 431–449.
- Young, J. E, Hawkins, R., Sharlin, E., & Igarashi, T. (2009). Toward acceptable domestic robots: Applying insights from social psychology. *International Journal of Social Robotics*, 1, 95–108.

Tables

Table 1

Descriptive Statistics for Variables

Variables	%	<i>n</i>	<i>M</i>	<i>SD</i>	<i>Range</i>	<i>n of items</i>	α
Acceptance of humanoid robot		104	28.99	5.39	17–42	9	.750
Acceptance of pet robot		220	33.51	6.33	11–45	9	.831
Acceptance of lifting robot		93	32.01	5.19	13–44	9	.788
Acceptance of telepresence robot		84	29.00	5.71	9–42	9	.789
Robot use self-efficacy		3377	4.19	0.77	1–5	3	.843
Age		3700	46.50	11.30	17–70		
Gender ^a		3685	0.05	0.23	0–1	1	
female	94.6	199					
male	5.4	3486					
Robot experience		3476	0.19	0.49	0–4	4	
Interest in technology and its development		3736	2.07	0.49	1–3	1	
General self-efficacy		3584	2.63	0.91	1–9	6	.814

Note. ^aGender: 0 = female, 1 = male.

Table 2

Summary of Regression Analysis for Variables, Humanoid Robot as a Dependent Variable (n = 104)

Variable	Model 1			Model 2			Model 3			Model 4		
	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE (B)</i>	β
Robot use self-efficacy	4.60	0.73	0.53***	4.86	0.74	0.56***	4.17	0.77	0.48***	4.15	0.78	0.48***
Age				0.04	0.040	0.08	0.02	0.04	0.05	0.03	0.04	0.06
Gender				-2.60	1.83	-0.12	-2.30	1.79	-0.11	-2.28	1.80	-0.11
Robot experience							0.69	0.60	0.10	0.70	0.60	0.10
Interest in technology and its development							2.04	0.98	0.18*	2.02	0.99	0.18*
General self-efficacy										-0.19	0.59	-0.03
R^2		.27			.28			.32			.31	
F for change in R^2		39.53			1.54			3.42			0.10	
		***						*				

Note. Dependent variable: Humanoid robot* $p < .05$. ** $p < .01$. *** $p < .001$

Table 3

Summary of Regression Analysis for Variables, Pet Robot as a Dependent Variable (n = 220)

Variable	Model 1			Model 2			Model 3			Model 4		
	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE (B)</i>	β
Robot use self-efficacy	2.94	0.58	0.33***	3.10	0.57	0.35***	3.00	0.61	0.34***	3.01	0.61	0.34***
Age				0.04	0.034	0.08	0.04	0.04	0.08	0.04	0.04	0.07
Gender				-3.87	1.63	-0.15*	-4.03	1.67	-0.16*	-3.85	1.68	-0.15*
Robot experience							-0.03	0.71	0.00	-0.05	0.71	0.00
Interest in technology and its development							0.50	0.87	0.04	0.45	0.87	0.04
General self-efficacy										0.58	0.47	0.08
R^2		.11			.13			.12			.12	
<i>F</i> for change in R^2		26.18			3.76			0.17			1.54	
		***			*							

Note. Dependent variable: Pet robot* $p < .05$. ** $p < .01$. *** $p < .001$

Table 4

Summary of Regression Analysis for Variables, Lifting Robot as a Dependent Variable (n = 93)

Variable	Model 1			Model 2			Model 3			Model 4		
	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE (B)</i>	β
Robot use self-efficacy	1.37	0.80	0.18	1.36	0.81	0.18	1.37	0.83	0.18	1.54	0.84	0.20
Age				-0.03	0.04	-0.09	-0.03	0.04	-0.09	-0.03	0.04	-0.09
Gender				-0.51	1.59	-0.04	-0.48	1.69	-0.03	-0.32	1.69	-0.02
Robot experience							-0.03	0.84	0.00	-0.13	0.84	-0.02
Interest in technology and its development							-0.07	1.16	-0.01	-0.27	1.17	-0.03
General self-efficacy										-0.83	0.65	-0.14
R^2		.02			.01			-.02			-.01	
F for change in R^2		2.95			0.34			0.00			1.64	

Note. Dependent variable: Lifting robot* $p < .05$. ** $p < .01$. *** $p < .001$

Table 5

Summary of Regression Analysis for Variables, Telepresence Robot as a Dependent Variable (n = 84)

Variable	Model 1			Model 2			Model 3			Model 4		
	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE B</i>	β	<i>B</i>	<i>SE (B)</i>	β
Robot use self-efficacy	3.32	0.76	0.44***	3.39	0.80	0.44***	2.07	0.81	0.27*	2.05	0.82	0.27*
Age				0.05	0.06	0.08	0.01	0.06	0.02	0.01	0.06	0.01
Gender				1.62	2.10	0.08	0.48	1.94	0.02	0.56	1.98	0.03
Robot experience							1.49	0.70	0.20*	1.50	0.71	0.20*
Interest in technology and its development							3.35	1.06	0.33**	3.38	1.07	0.33**
General self-efficacy										0.17	0.63	0.03
R^2	.18			.17			.31			.30		
F for change in R^2	19.22			0.71			8.54			0.07		
	***						***					

Note. Dependent variable: Telepresence robot.

* $p < .05$. ** $p < .01$. *** $p < .001$

APPENDIX A

English translation of the nine statements used in the four robot-specific dependent variables.

1. I think it's a good idea to use the [robot] (Attitude towards technology)
2. I think the [robot] would be useful in my job (Perceived usefulness)
3. I think I can use the [robot] without any help (Perceived ease of use)
4. Working with the [robot] would be pleasant (Perceived enjoyment)
5. I would not be worried about the safety of using the [robot] (Trust)
6. I think the [robot] can be adapted to what I need (Perceived adaptivity)
7. I know enough of the [robot] to make good use of it (Facilitating conditions)
8. I would not be afraid to make mistakes with the [robot] (Anxiety)
9. Pleasant/smooth interaction (Perceived sociability/operating friendliness)

Response options: 5-point Likert scale from “*totally disagree*” to “*totally agree*”.