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When Robots Enter Our Workplace: Understanding Employee Trust in Assistive Robots

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Short Paper

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Abstract

This study is about assistive robots as internal service provider within the company Merck KGaA and examines how the physical appearance of a service representative (humanoid robot, android robot, human) affects employees' trust. Based on the uncanny valley paradigm, we argue that employees' trust is the lowest for the android robot and the highest for the human.

Further, we will examine the effects of task complexity and requirements for self-disclosure on employees' trust in assistive robots. According to script theory and media equation theory, we propose that high task complexity and high requirements for self-disclosure increase employees' trust.

We developed a research design to test our model by deploying a humanoid robot and an android robot within a company as robotic assistants in comparison to a human employee. In a next step, we will run a corresponding study with 300 employees.

Keywords: Assistive robots, trust, robots at workplace, task complexity, self-disclosure

Relevance and Research Questions

The interplay of human and robotic workers promises flexibility, savings and new competitive capabilities. Thus, the penetration of assistive robots is "designed to support and service humans through physical and social interactions" (Ivanov et al. 2017, p. 3) in various industries. Assistive robots are superior to previously applied technologies, such as self-service technologies, because "in the context of social interaction [...] robot[s] can create some degree of automated social presence (ASP) during the services encounter, which refers to the ability to make consumers feel that they are in the company of another social entity" (Wirtz et al. 2018, p. 909). This enables the establishment of an improved human-robot relationship and a pleasant service experience within companies (Ivanov et al. 2017; Wirtz et al. 2018). Some researchers even argue that this effect can be intensified by robots' appearance (Cheetham et al. 2014). According to the uncanny valley paradigm, human trust toward robots depends on its appearance (Mori 1970).

Although the application of assistive robots is promising for reasons as described above, the use of robots in companies is still sparse. This can be attributed to the insufficient research on human-robot interaction (HRI) within the organizational context. Although, there are some studies focusing on psychological aspects of HRI, such as resistance toward robots in the organizational context (Osawa et al. 2017, Thomas et al. 2016) or the social impact of a robot co-worker in industrial settings (Sauppé and Mutlu 2015), overall research offers companies too little knowledge to assess the usefulness and appropriateness of robots in their companies (Wirtz et al., 2018). In particular, there is insufficient knowledge about psychological responses of employees to robots or factors defining a successful HRI. This raises questions such as about mechanisms affecting employee trust during a HRI. To enable assistive robots to interact effectively with employees and improve employee-robot collaboration, it is necessary "to expand our understanding of the psychological aspects of these exchanges" (Broadbent et al. 2007, p. 3703). Finally, this would contribute to the ultimate goal and challenge of robotics "to find ways that social robots can participate in the richness of human society" (Fong et al. 2003, p. 44).

Therefore, this study compares employee trust in assistive robots varying in their human-likeness, defined as the "degree of physical humanlike similarity" of a robot (Cheetham et al. 2013, p. 108) and examines contingency factors that may affect employees' trust in robots. Hence, following research questions are raised: 1) *How does a robot's physical appearance affect employee trust in an assistive robot?* 2) *How does task complexity and requirement of self-disclosure affect employees' trust in an assistive robot?*

With an experimental study, we investigated employees trust in assistive robots during HRI in a real company setting with 300 employees at the German headquarters of the pharmaceutical company Merck KGaA. For this purpose, the humanoid robot Pepper and the android robot "Elenoide" serve as HR experts to consult employees about their personal HR development perspectives. The HRIs are then compared with human-human interactions with a real HR expert of the company in which the experiments take place.

Theoretical Background

Increasing debates about human-like robots have prompted researchers to leverage the uncanny valley paradigm (Mori 1970). It assigns robots to different levels of human-likeness, with the lowest level including *industrial robots* to which humans have a low affinity (Mori et al. 2012). The next level of human-likeness refers to *humanoid robots*. They "often come with extremities like arms, legs or a head but still have an overall mechanical look" (Mara and Appel 2015, p. 329). In contrast to industrial robots, their designs are driven by appearance considerations. Although humans often perceive a human-like appearance of robots as positive, human perceptions also may be dominated by fear and reluctance when that human-likeness passes a certain level (Ramey 2005). This zone represents the "uncanny valley," which "refers to a state of perceptual or cognitive experience at which an increasingly human-like figure becomes strange, rather than more familiar or acceptable" (Ramey 2005, p. 8) and is inhabited by so-called *android robots*. An android is "an artificial system designed with the ultimate goal of being indistinguishable from humans in its external appearance and behavior" (MacDorman and Ishiguro 2006, p. 298). Finally, the highest level of humanness is associated with *real humans*. According to the uncanny valley paradigm, humans feel the greatest likability for real humans, because they create minimal dissonance and uncertainty and are more familiar than any robot. This study relies on the uncanny valley paradigm to examine the differences that employees perceive between humans and different types of assistive robots, as well as the associated level of trust they display in each case.

Trust is the "implicit set of beliefs that the other party will refrain from opportunistic behavior and will not take advantage of the situation" (Ridings et al. 2002, p. 275). We rely on a well-established IS trust model to capture employees' trust in the robot assistant using three trusting beliefs reflecting their perception of the robot's competence, benevolence and integrity (McKnight et al. 2002). It is important to build up employee trust in the robot, as employees might have reservations regarding the collaboration with a technology due to uncertainty and perceived risks (McKnight et al. 2002). Employee trust helps to overcome these reservations and encourages employees to collaborate with the assistive robot, whereas a lack of trust keeps employees from collaborating (Bhattacherjee 2002).

From a practical point of view, we want to find out what type of tasks are suitable to be supported by assistive robots. Therefore, we vary the tasks in terms of task complexity (Liu and Li 2012) and the requirement for self-disclosure (Cozby 1973).

Perceived task complexity is "a function of the number of elements of which the task is composed of and the relationships between those elements of a task [...] as well as the resource requirements" associated with a task (Liu and Li 2012, p. 554-555). Accordingly, task complexity has two components, a structural component representing the number of elements (Stock 2006) and a resource component representing cognitive efforts and complex decision-making (Wegge et al. 2008). Robots are increasingly used for complex tasks and research shows that human-robot team performance is most sensitive to complexity (Senol 2019). Therefore, it is necessary to take the effects of task complexity into account.

Self-disclosure is defined as "any information about himself which Person A [the employee] communicates verbally to Person B [the HR representative]" (Cozby 1973, p. 73). Studies show evidence of increased privacy concerns among users of technologies that affect self-disclosure toward technologies (Alashoor et al. 2017) such as assistive robots. Therefore, it is worth considering the effects of requested self-disclosure on employee trust in this setting.

Framework and Hypotheses of the Study

Figure 1 depicts the framework of the study. The independent variable is the physical appearance (humanoid vs. android vs. human). This study examines the effects on employee trust in robots as dependent variable and considers moderating effects of task complexity and self-disclosure requirement.

An employees' trust of a robot might differ for HRI with various robots and human-human interactions, as predicted by the uncanny valley paradigm (Mori 1970). Uncanny valley theorists argue that humans sense greater familiarity with humans than non-human entities, such as humanoid robots (Cheetham et al. 2014; Moore 2012). Their familiarity with humanoid robots is lower, because the expressions shared by these robots are more difficult for human to interpret. Studies have shown that familiarity leads to trust in electronic systems (Komiak and Benbasat 2006) as well as trust on an organizational level (Guliati 1995). Accordingly, employees' trust in a humanoid and in an android robot might be weaker than trust in humans. Formally,

H1. Employees' trust in robots is lower (a) in humanoid robots and (b) in android robots than in humans.

Furthermore, the uncanny valley predicts that humans perceive more human-looking robots with a rather technical appearance as generally positive. Overly human-looking robots, however, cause the human's perception of the robot to become negative (Cheetham et al. 2014). Thus, we argue:

H2. Employees' trust in android robots is lower than employees' trust in humanoid robots.

To develop hypotheses regarding contingency effects, we rely on script theory. While uncanny valley focusses on the physical appearance, script theory predicts that social exchanges reflect the involved parties' roles (Parker and Ward 2000), and each role is associated with a script that consists of "cognitive structures that describe appropriate sequences of behavior for interaction" (Price et al. 1995, p. 84). Script theory has been applied previously in management literature, such as the interaction between employees and their customer to predict customer behaviors, because it sheds light on customers' expectations and decision-making processes (Searleman and Hermann 1994). In particular, customers' and service providers' expectations tend to be similar and comparable when they share common role expectations, based on a well-defined script, which creates script congruence.

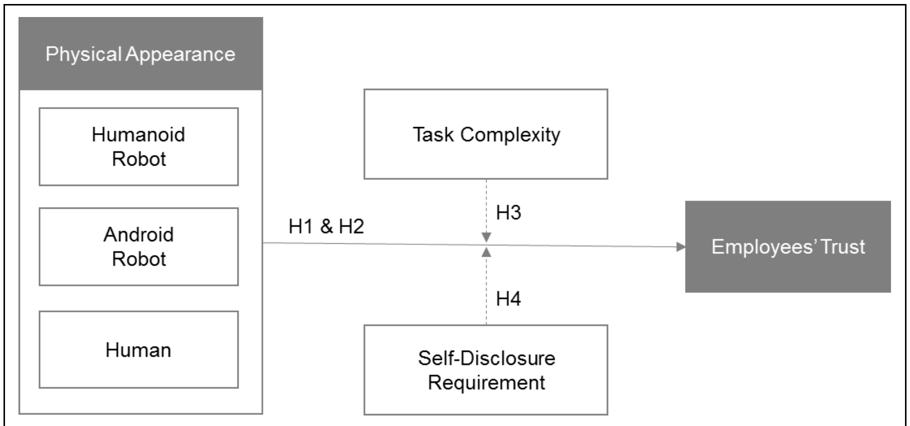


Figure 1. Framework of the Study

For this study, we argue that employees also rely on scripts when they interact with an assistive robotic agent, in a way similar to the mechanisms that underlie human–human interactions with internal service encounters. Yet humans may not have developed a unique script for internal service encounters with robots, because they lack sufficient prior experience with these emerging technologies.

According to media equation theory (Nass and Moon 2000), they might apply existing social rules and expectations to machines and display social reactions. The more elaborated the communication is with assistive robots, the stronger is the application of social rules and the attribution of human characteristics toward the assistive robot (Nass and Moon 2000). We argue that both, task complexity and the request for self-disclosure, lead to a more elaborated interaction. Task complexity rises information seeking and leads to a richer interaction. Disclosing oneself to the assistant leads to an increased application of socials rules toward the assistive robot.

Both are supposed to increase employees' trust in the robot because for these constellations, humans are supposed to simply "assign human traits and characteristics to computers and apply social scripts—scripts for human-human interaction" (Nass and Moon 2000, p. 83). Thus,

H3. Employees' trust in robots is higher during human-robot interactions for tasks with high task-complexity as opposed to tasks with low complexity.

H4. Employees' trust in robots is higher during human-robot interactions for tasks with high requirement for self-disclosure as opposed to tasks with low requirement for self-disclosure.

Preparation and Validation

We created an experimental vignette for a HRI in which the robot served as a HR expert to consult employees during an information day for employees. To gain a realistic setting for the participating employees that still meets the requirements for a laboratory experiment, the preparation occurred in multiple steps.

In the study we will rely on the humanoid robot pepper from Softbank Robotics and the android robot Elenoide from A-Lab in Japan. We programmed and validated both to be able of showing the most basic emotions. In the second step, we developed the vignette for the experiment. Specifically, we developed an experimental vignette to assess the effects of task complexity and the requested self-disclosure on the interaction with the robots. In a third step, we integrated the robot with a chatbot and programmed the different scripts for the HRI. In a fourth step, we pretested the experiment in a laboratory setting. In a final step, we conducted the experiments in a laboratory setting.

Humanoid Robot

In our experimental study, we will rely on the Pepper robot, as it is a widely used humanoid robot and has already been used in several studies (Csapo et al. 2012; Domingues et al. 2011). The Pepper robot has a tablet with a touchscreen on its chest. We programmed several emotional behaviors to the robot. Therefore, we applied a two-step approach to come up with specific emotional behaviors that were validated subsequently. First, we relied on extant literature in psychology (Pease 1981) and robotic research that suggested various behavioral outputs for emotional expressions for humanoid robots (Andreasson et al. 2017; Breazeal 2000,). Second, we conducted a web search identifying 100 pictures for each of the five emotions (neutral, happiness, positive surprise, anger, and frustration). Based on these pictures, we programmed the two most typical bodily expressions for each emotion.

Afterwards we validated the programmed emotions with a set of 321 students (75% male; mean age 19.51, SD = 1.90). The respondents clearly identified those bodily and verbal expressions meant for expressing emotions. The appreciation for Pepper's emotional expressions of happiness (74%), positive surprise (72%), anger (88%) and frustration (84%) were on an acceptable level.

Android Robot

The android robot is 173 cm tall and weighs 65 kg. It has 49 degrees of freedom to demonstrate emotions and gestures and shows high similarity to a human, as it is designed according to a human model. By using compressed air to power the robot, quiet movements and soft reactions to external resistances are accomplished. With the combination of the anthropomorphic look and the capability to perform human-like facial expression and gestures, this android robot shows one of the highest potential worldwide for robot to imitate humans.

We wanted to base the android's emotions on real human emotions. Therefore, we asked two actors to show a few expressions for each of the emotions of happiness, anger, boredom, calmness, fear, sadness, and surprise. We recorded all expressions for each emotions and validated them with a sample of 36 students to identify the best representations of each emotion with high recognition rates above 80%. We used these emotional expressions as basis for the programming of the android robot and tried to reproduce the human emotions as much in detail as possible with the android robot.

We validated the android's emotional expressions and asked a total sample of 132 students (age ranging from 19-42 years with an average of 23.6 years; 57% male; 50% technical background) to rate the emotions. We showed the videos to students in classroom and asked them to classify the displayed emotions. In total, the respondents clearly identified the emotions consisting of gestures and mimics for the emotions happiness (91%), anger (87%), boredom (95%) and calm (87%). However, the emotions fear, sadness and surprise were not recognized that clearly in the first validation. Therefore, we refined the mimics and gestures for these emotions, run a second round of validation with 72 students, and reached improved values for the emotions of fear (91%), sadness (90%) and surprise (97%).

Vignette Development for the Experimental Study

As described previously, we attempt to manipulate two variables: high vs. low task complexity and requirement for self-disclosure. To manipulate these conditions and to ensure a comparable situation for all participants that is as realistic as possible, we relied on an experimental vignette methodology (Aguinis and Bradley 2014). Experimental vignettes "consist of presenting participants with carefully constructed and realistic scenarios to assess dependent variables [...], thereby enhancing experimental realism and also allowing researchers to manipulate and control independent variables" (Aguinis and Bradley 2014, p.351). We use the paper people study type of experimental vignette method, because it aims at explicit behavioral expressions and outcomes. We wanted the participants to put themselves into the respective scenario and to contribute the presented role to the HRI. During this experiment, the employees had to put themselves into their role as employee of this specific company they were working for and to interact with the robot with the purpose to get advice about HR topics.

During the vignette development, it therefore was important for us to determine the most frequent HR topics for the employees. Methodologically we rely on grounded theory for our interview study (Bowen 2008). This method attempts to evolve the interview guideline during the interview study through continuous interplay between analysis of completed interviews and the adaption of guideline for further interviews (Strauss and Corbin 1994). It ends up in a state of saturation at a certain point as new interviews mainly confirm current findings without new contribution.

For this study, we conducted several interviews with HR experts of the company to identify the most important HR topics. The interviews with the HR experts indicated soft-skill trainings for personal development and work-life balance were particularly relevant. Further, we asked for a typical job profile that most employees could identify with to be able to create the most realistic situation in the study. Based on these insights, we developed an experimental vignette together with HR experts from the company. In a next step, we again contacted the HR experts and asked them to rate and improve the existing vignette. We constantly refined our vignette throughout the interviews and had six major versions of the vignette. However, after the last three interviews there were no major changes needed anymore, as the feedback was constantly very positive. In total, we conducted in-depth interviews with ten HR experts. The interview partners had an average age of 35.5 years ranging from 29 to 57 years and on average one interview took 27 minutes.

After the HR experts had ensured the relevance of the topics, we built two different versions significantly varying in terms of complexity. We varied the task complexity without changing the topics of the vignette. In our validation study, we wanted to make sure, that both variations are significantly different in terms of task complexity and that participants consider the vignette as highly realistic and comprehensible.

The vignette was discussed with eleven external practitioners and scientists with an average age of 30 years ranging from 21 to 52 years. The vignette was considered as clearly comprehensible ($M = 5.33$, $SD = 1.86$, 7-point Likert-scale) and highly realistic ($M = 5.73$, $SD = 1.20$). In terms of resource complexity ($\alpha = .79$), the complex vignette ($M=5.57$, $SD=0.94$, 7-point Likert-scale) was considered significantly more complex ($\Delta M = 1.69^*$, $p = .03$) than the simple vignette ($M = 4.08$, $SD = 1.05$) (Kyndt et al. 2011; Wegge et al. 2008). For structural complexity ($\alpha = .74$) we found similar significant differences ($\Delta M = .88^*$, $p = .001$).

The requirement for self-disclosure will be realized by the HR representative asking for personal information.

Experimental Pilot Study

Within the company, there already existed a chatbot based on IBM Watson. We trained the chatbot and added more information about the topics from the vignette to allow more profound conversations about the chosen topics.

This pilot study was carried out in a lab associated with the authors' university. We applied a sample with 25 students with various majors (psychology, management, and engineering) with an average age of 22.3 years ranging from 18 to 44 years with 60% male participants. On average, the conversation with the android robot took 10.6 minutes.

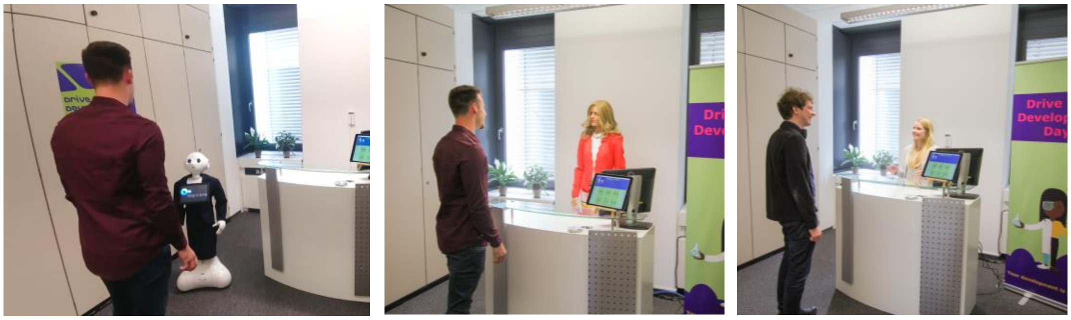
The participants received a printed version of the vignette and had to summarize their task. Then the experimenter made sure that the participant understood the vignette correctly. After that, the participant was guided into a room with the android robot that was connected with the chatbot. The participants were alone with the robot and had to fulfill their task and get consultation from the robot regarding trainings and work-life balance topics. In the end, we asked the participants to rate the interaction with the robot in a short questionnaire.

The vignette was rated high in terms of comprehensibility ($M = 4.44$, $SD = 0.65$, 5-point Likert-scale) and realistic ($M = 4.12$, $SD = 0.83$). The verbal expression of the robot was considered quite natural ($M = 4.00$, $SD = .71$) and the robot was friendly ($M = 4.32$, $SD = 0.56$) and clearly understandable ($M = 4.20$, $SD = 1.00$). All participants were able to fulfill their task and to receive the required information from the android robot. However, we made some further improvements due to the weaknesses shown in the pilot study.

Main Study

Experimental Setup

The experiment will be carried out in the context of the *Drive Your Development Days* at Merck. Visitors to the *Drive Your Development Days* can ask the humanoid robot (Figure 2a), the android robot (Figure 2b) or the human HR representative (Figure 2c) questions about training opportunities and about work-life balance topics at Merck. Each participant will interact separately with the HR representative during the study. To provide a greater amount of natural noise (Aguinis and Bradley 2014), the room will be airconditioned and designed with the company's equipment. By using a confederate that looks similar to the android robot, we will control another possible source of noise.



(a) Humanoid Robot (b) Android Robot (c) Human HR Representative

Figure 2. Experimental Setting at the Company

We will apply a 3 x 3-research design. The HR representative will be randomly chosen from the three options in Figure 2. Further, we will randomize the task in the vignette: there is a simple task, a complex and a task with request for self-disclosure as shown in Table 1. To examine the different experimental conditions we chose a between-subject design to avoid learning effects. As we are just interested in the effects of the appearance, the two robot types will be connected to the same IBM Watson chatbot and therefore offer exactly the same conversation. The human representative will be trained on the same script as the robots to give comparable answers.

The manipulation contains of nine alternative conditions, of which only one will be given to each participant. The instructions will differ with respect to the task complexity, the request for self-disclosure by the HR representative and the type of HR representative as shown in Table 1:

Table 1. Experimental Conditions

	Simple Task	Complex Task	Task with Request for Self-Disclosure
Humanoid Robot	N = 30	N = 30	N = 30
Android Robot	N = 30	N = 30	N = 30
Human HR Representative	N = 30	N = 30	N = 30

Sample and Measurement

We will invite all employees at the headquarters via the company's intranet and advertising at the cafeteria to participate in the study. We want to get 270 participants from different departments, including white-collar and blue-collar workers. The software G*Power 3.1.9.4 suggests a total sample size of N = 270 for an effect size of $f = .3$, an alpha error of $\alpha = .05$ and a power of $(1 - \beta) = .8$ (Faul et al. 2009). Therefore we are planning to have at least N = 30 participants per condition.

Prior and after the interaction with the HR representative, the participants will have to fill out an online-based questionnaire about controls such as their personality, prior experiences with robots and demographic data. Furthermore, we will ask for expectations toward the robot and afterwards for the actual perception of the interaction. Besides these subjective self-ratings, we rely on further data sources for the evaluation of participants' emotions within the interaction. We will apply the E4 wristband from Empatica to record physiological data such as heart rate and electro dermal activity. These E4 wristband data show similar accuracy in terms of emotion recognition compared with laboratory sensors (Ragot et al. 2017).

Moreover, all experimental interactions will be recorded with HD cameras and a circular array microphone. All participants will be informed in advance about the collection of physiological data and the video recordings and we already clarified our experimental data collection with data protection experts and the company's workers council. The video recording provides the opportunity to control for speech characteristics by third party raters afterwards. In addition to emotion recognition and speech characteristics, we will add age, gender and selected job characteristics and experiences as control variables. The measurement scales are adopted from prior literature, generally using 7-points Likert scales. While self-disclosure is measured after the interaction with 7 items (Reis and Wheeler 1991), task complexity is measured with an 1-item scale based on Kyndt et al. (2011). Propensity to trust (3 items, Dinev et al. 2006) is measured before the interaction. Trust is measured after the interaction, assessing the three most utilized types of trusting beliefs (McKnight et al. 2002): benevolence (3 items), integrity (4 items), and competence (4 items).

Conclusion

We proposed a study framework and developed an experimental design within an internal company-setting to examine how physical appearance and contingency factors (task complexity, self-disclosure requirement) affect employee trust in an either robotic or human HR representative. Based on uncanny valley paradigm we will test the trust of different robot types and compare it to a human HR representative. Further, we will take moderating effect from contingency factors into account.

However, some limitations of this study must be pointed out. In this study, we focus only on one industry type, which means that distortion effects concerning the employees' response must be considered. Moreover, this study does not cover up familiarization effects that can occur in long-term HRI. Hence, the findings of this study are only partly generalizable.

Our study contributes to extant research, by filling first gaps in the HRI research as claimed by many researchers. Therefore, we examined the effect of contingency variables on employee-robot trust. This offers insights for an effective robot design that also considers privacy aspects. Moreover, this study will deliver a profound validation for future mixed teams of robots and employees at the workplace. Findings from the examined company will allow other firms to benefit from the insights regarding the placement of robots within a company and consequently show how to integrate effectively assistive robots into the future of work.

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References

Aguinis, H., and Bradley, K. J. 2014. „Best practice recommendations for designing and implementing experimental vignette methodology studies," *Organizational Research Methods* (17:4), pp. 351-371.

Alashoor, T., Han, S., and Joseph, R. C. 2017. "Familiarity with Big Data, Privacy Concerns, and Self-disclosure Accuracy in Social Networking Websites: An APCO Model," *CAIS* (41:4), p. 62-96.

Bhattacherjee, A. 2002. "Individual trust in online firms: Scale development and initial test," *Journal of management information systems* (19:1), p. 211-241.

Bowen, G. A. 2008. „Naturalistic inquiry and the saturation concept: a research note," *Qualitative research* (8:1), p. 137-152.

Broadbent, E., MacDonald, B., Jago, L., Juergens, M., and, Mazharullah O. 2007. "Human Reactions to Good and Bad Robots," *Proceedings of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Diego, CA, USA, Oct 29 - Nov 2.

Chao, Georgia T., and Kozlowski, Steve W. 1986. "Employee perceptions on the implementation of robotic manufacturing technology," *Journal of Applied Psychology* (71:1), pp. 70-76.

Cheetham, M., Pavlovic, I., Jordan, N., Suter, P., and Jancke, L. 2013. "Category processing and the human likeness dimension of the uncanny valley hypothesis: Eye-tracking data," *Frontiers in Psychology* (4), p. 1-12.

Cozby, P. C. 1973. "Self-disclosure: a literature review," *Psychological bulletin* (79:2), p. 73-91.

Dinev, T., Bellotto, M., Hart, P., Russo, V., Serra, I., & Colautti, C. 2006. "Privacy calculus model in e-commerce–a study of Italy and the United States," *European Journal of Information Systems*, (15:4), p. 389-402.

Domingues, E., Lau, N., Pimentel, B., Shafii, N., Reis and L., Neves, A. 2011. "Humanoid behaviors: from simulation to a real robot," *Progress in Artificial Intelligence / EPIA* (11), p. 352–364, Springer.

Faul, F., Erdfelder, E., Buchner, A., and Lang, A.-G. 2009. „Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses," *Behavior Research Methods* (41), p. 1149-1160.

Fong, T., Nourbakhsh, I., & Dautenhahn, K. 2003. "A survey of socially interactive robots," Robotics and Autonomous Systems (42:3), p. 143–166.

Ivanov, S., Webster, C., and Berezina, K. 2017. "Adoption of robots and service automation by tourism and hospitality companies," *INVTUR Conference*, p. 17–19 May 2017, Aveiro, Portugal.

Komiak, S. Y. and Benbasat, I. 2006. "The effects of personalization and familiarity on trust and adoption of recommendation agents," *MIS quarterly* (30:4), p. 941-960.

Kyndt, E., Dochy, F., Struyven, K., and Cascallar, E. 2011. "The perception of workload and task complexity and its influence on students' approaches to learning: A study in higher education," *European Journal of Psychology of Education* (26:3), p. 393-415.

Liu, P., and Li, Z. 2012. "Task complexity: A review and conceptualization framework," *International Journal of Industrial Ergonomics* (42:6), p. 553-568.

MacDorman, K. F., and Ishiguro, H. 2006. "The uncanny advantage of using androids in cognitive and social science research," *Interaction Studies*, (7:3), p. 297–337.

McKnight, D. H., Choudhury, V., and Kacmar, C. 2002. "Developing and validating trust measures for e-commerce: An integrative typology," *Information systems research* (1:3), p. 334-359.

Mara, M., and Appel, M. 2015. "Science fiction reduces the eeriness of android robots: A field experiment," *Computers in Human Behavior (48)*, p. 156-162.

Mori, M. 1970, "Bukimi no Tani [The Uncanny Valley]," *Energy,* 7 (4), pp. 33–35.

Nass, C. and Moon, Y. 2000. "Machines and Mindlessness: Social Responses to Computers," *Journal of Social Issues* (56:1), p. 81–103.

Osawa, H., Ema, A., Hattori, H., Akiya, N., Kanzaki, N., Kubo, A., ... and Ichise, R. 2017. "What is real risk and benefit on work with robots?: From the analysis of a robot hotel," *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction,* p. 241-242.

Parker, C. and Ward, P. 2000. "An Analysis of the Role Adoptions and Scripts During Customer-to-Customer Encounters," *European Journal of Marketing* (34:3/4), p. 341–358.

Price, L. L., Arnould, E. J., and Tierney, P. 1995. "Going to Extremes: Managing Service Encounters and Assessing Provider Performance," *Journal of Marketing* (59:2), p. 83–97.

Ragot, M., Martin, N., Em, S., Pallamin, N., and Diverrez, J. M. 2017. „Emotion recognition using physiological signals: laboratory vs. wearable sensors," *International Conference on Applied Human Factors and Ergonomics,* p. 15-22.

Ramey, C. H. 2005. "The uncanny valley of similarities concerning abortion, baldness, heaps of sand, and humanlike robots," *Proceedings of Views of the Uncanny Valley Workshop: IEEE-RAS International Conference on Humanoid Robots,* p. 8–13. Tsukuba, Japan.

Reis, H. T., and Wheeler, L. 1991. "Studying Social Interaction with the Rochester Interaction Record," *Advances in Experimental Social Psychology* (24), p. 269–318.

Ridings, C. M., Gefen, D., and Arinze, B. 2002. "Some antecedents and effects of trust in virtual communities," *The Journal of Strategic Information Systems* (11:3), p. 271-295.

Sauppé, A. and Mutlu, B. 2015 "The social impact of a robot co-worker in industrial settings." *Proceedings of the 33rd annual ACM conference on human factors in computing systems*.

Searleman, A. and Herrmann, D. 1994. "Memory from a Broader Perspective," New York, McGraw-Hill.

Strauss, A. and Corbin, J. 1994. "Grounded Theory Methodology: An Overview" in N.K. Denzin and Y.S. Lincoln (eds) Handbook of Qualitative Research. Thousand Oaks, CA: Sage Publications.

Thomas, C., Stankiewicz, L., Grötsch, A., Wischniewski, S., Deuse, J., and Kuhlenkötter, B. 2016. "Intuitive work assistance by reciprocal human-robot interaction in the subject area of direct human-robot collaboration," *Procedia CIRP (44)*, p. 275-280.

Wegge, J., Roth, C., Neubach, B., Schmidt, K. H., and Kanfer, R. 2008. „Age and gender diversity as determinants of performance and health in a public organization: The role of task complexity and group size," *Journal of Applied Psychology* (93:6), p. 1301-1313.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S. and Martins, A. 2018. "Brave New World: Service Robots in the Frontline," *Journal of Service Management* (29:5), p. 907-931.