

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/350866851>

A social cognition perspective on autonomous technology

Article in *Computers in Human Behavior* · April 2021

DOI: 10.1016/j.chb.2021.106815

CITATIONS

0

READS

38

Some of the authors of this publication are also working on these related projects:



Smart Government [View project](#)



Full length article

A social cognition perspective on autonomous technology

Ruth Frischknecht

Smart Government Lab at the Institute of Systemic Management and Public Governance, Dufourstrasse 40a, University of St.Gallen, Switzerland

ARTICLE INFO

Keywords:

Human-computer interaction
 Technical autonomy
 Social cognition
 Mind perception
 Survey experiment

ABSTRACT

The last several years have been characterized by an increasing autonomization of technology. Advanced technologies are now capable of learning and interacting. These capabilities expand the scope in which technology can be used. As a result, these increasingly autonomous machines and programs are completing an ever-growing number of tasks in collaboration with humans. This is why it is important to determine whether increasing levels of autonomy affect how technical systems are perceived by their human counterparts. An online survey experiment using vignettes to describe technical systems with varying levels of autonomy was employed to test the effects of technical autonomy on the dimensions of social cognition (i.e., warmth and competence) and mind perception (i.e., experience and agency). The findings show that increasing levels of technical autonomy impacted how the technical systems were socially perceived. More specifically, the findings suggest that the more autonomous a technical system is, the more competence and agency it will be ascribed. Conversely, increasing levels of technical autonomy had no effect on the ascription of warmth and experience. These results highlight that technical autonomy is relevant to and effectively shapes social judgements regarding technology.

1. Introduction

Advanced technical systems are widespread in today's world taking over more and more tasks in our society. For example, advanced algorithms are used in personnel selection (van Esch, Black, & Ferolie, 2019) and the assessment of offenders (Dressel & Farid, 2018). Social robots care for the elderly and educate children (Broadbent, 2017). Their ability to complete such complex tasks changes the relationship between humans and machines. Machines are no longer mere tools (Rammert, 2011), but rather a type of companion (de Visser, Pak, & Shaw, 2018) or teammate (McNeese, Demir, Cooke, & Myers, 2018; Seeber, Bittner, et al., 2020). Their role has changed from one of decision supporter to that of actual decision maker (Nissen & Sengupta, 2006).

For technical systems to fulfill such complex tasks, machines must be able to respond to situations for which they have not been pre-programmed (Araujo, Helberger, Kruikemeier, & de). As a result, such systems are described as becoming more intelligent and autonomous (Corti & Gillespie, 2016; Seeber, Bittner, et al., 2020). Although there is no universal definition of technical autonomy per se, scholars seem to agree on some of its prerequisites. Adaptability and machine learning are considered core features of autonomous technology (de Visser et al., 2018; Jordan & Mitchell, 2015; Seeber, Waizenegger, et al., 2020). The capacity to interact with and enlarge their source data is another feature of technical autonomy (de Visser et al., 2018; Jordan & Mitchell, 2015;

Seeber, Waizenegger, et al., 2020). Yet this does not mean that every technical system is equipped with the characteristics that shape technical autonomy. Rather, current developments include different technical systems that operate on various levels of technical autonomy. This means that technical autonomy should not to be understood as a binary category (i.e., a technical system is either autonomous or non-autonomous) but rather as a gradual property. According to this view, technical autonomy consists of different levels (de Visser et al., 2018; Endsley, 2017; Simmler & Frischknecht, 2021) or as comprised of various dimensions (Beer, Fisk, & Rogers, 2014). This suggests that there can be different types or levels of technical autonomy. Endsley (2017), for example, introduced the notion of "semi-autonomous systems" to indicate that technology today does not reach full autonomy, nor is it strictly determined. Simmler and Frischknecht (2021) proposed a taxonomy for capturing technical autonomy that is comprised of five consecutive levels, providing an even more precise conception of how increasing technical autonomy can be mapped and described. It seems that the understanding of what technical autonomy is, is becoming clearer and more nuanced. However, the focus of the work cited above lies mainly on technology, or put differently, on the machine part of the human-machine collaboration.

The implementation of increasingly autonomous technical systems is associated with a wide array of social questions (Morris, Schlenoff, & Srinivasan, 2017; Rahwan et al., 2019). This calls for a more thorough

E-mail address: ruth.frischknecht@unisg.ch.

<https://doi.org/10.1016/j.chb.2021.106815>

Received 23 January 2021; Received in revised form 23 March 2021; Accepted 5 April 2021

Available online 10 April 2021

0747-5632/© 2021 The Author(s).

Published by Elsevier Ltd.

This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

understanding of how people respond to them, especially as the actions of autonomous technical agents are becoming more intractable, opaque and difficult to comprehend (Rahwan et al., 2019). For example, it is important to explore the extent to which increasingly autonomous machines are seen as responsible for their actions (Awad et al., 2020; Banks, 2019) and whether decisions made by autonomous algorithms are seen as trustworthy or fair (Hoddinghaus, Sondern, & Hertel, 2021; Lee, 2018). These studies highlight that it not only matters what the machine is objectively capable of, but rather how people subjectively perceive technical system and their actions. This is further illustrated by Lee (2018), who found that the actions of an algorithm mattered as much as what people thought the algorithm was capable of doing, when those people were asked to judge its trustworthiness and fairness. From this, it follows that people's perceptions of technical systems play an important role in human-machine interactions. In fact, the significance of such perceptions has been emphasized in the literature on human-machine (Araujo et al., 2020; Lee, 2018; Sundar, 2020) and human-robot interaction (Dautenhahn, 2007). Despite the recognition that people's perceptions of technology are relevant and important, little is known regarding if and how increasing levels of autonomy shape such perceptions. Therefore, this research aims to fill this gap by systematically exploring *whether and how technical autonomy shapes social perceptions*.

2. The social perception of technology

Various studies have shown that humans treat, perceive, and interact with technologies as if they are social actors (for an overview see e.g. Reeves & Nass, 1996). For example, research has found that people apply social norms such as politeness when interacting with computers (Nass, Moon, & Carney, 1999) and rely on gender stereotypes (Nass, Moon, & Green, 1997). Initial work in this area focused on computers, technical systems unable to learn or increase their source data, and thus machines that operate at a rather low level of autonomy. These findings have been replicated with more sophisticated technical agents such as chatbots and robots, in the former offering evidence that people tend to interact with them as if they are human (Corti & Gillespie, 2016) and in the latter categorizing them according to gender stereotypes (Eyssel & Hegel, 2012). Thus, people react socially to technical agents, regardless of whether they are simple computers or advanced chatbots.

This tendency to perceive and treat non-human entities such as computers and robots as if they are human is called anthropomorphism (Epley, Waytz, & Cacioppo, 2007). Anthropomorphizing non-human entities is a highly adaptable heuristic for making sense of one's environment (Epley et al., 2007). Children and adults alike describe a wide range of non-human entities and phenomena (such as animals or the weather) in anthropomorphic ways (Zlotowski, Proudfoot, Yogeewaran, &). Voice (Schroeder & Epley, 2016), movement patterns (Broadbent, 2017), and facial cues (Kim, Zhang, & Park, 2018) have all been found to reinforce the tendency to anthropomorphize technical agents. However, anthropomorphism only appears on an implicit level; when participants were asked explicitly if they would ascribe human-like characteristics to robots, they said they would not (Zlotowski et al., 2015). Thus, anthropomorphizing technical agents is considered an unintentional process that happens automatically (Epley et al., 2007). From this, it follows that people tend to attribute human characteristics to technical systems and treat technical systems like social actors. For this reason, the dimensions of social cognition, as well as the dimensions of mind perception, are worthy of closer examination because both capture social perceptions in a very basic manner.

In the field of social cognition, it is well-recognized that people perceive other entities, usually other people or groups of people, in terms of warmth and competence; together, these perceptions comprise the universal dimensions of social cognition (Fiske, 2018; Fiske, Cuddy, & Glick, 2007). The warmth dimension describes the perceived intent of an entity and includes ascriptions of friendliness and helpfulness, whereas the competence dimension describes the perceived ability of an

entity and includes ascriptions of intelligence and efficacy (Fiske et al., 2007). Findings in the field of social cognition research have already been applied to human-machine interactions. The Robotic Social Attributes Scale, an instrument for measuring people's judgment of robots, draws upon these two universal dimensions of social cognition (Carpinella, Wyman, Perez, & Stroessner, 2017). However, no general pattern of warmth and competence ascriptions to technical systems can be inferred from the literature. On the one hand, there is evidence that robots are ascribed more competence than warmth (Pan, Croft, & Niemeyer, 2018). On the other hand, Kim, Schmitt, and Thalmann (2019) found in their study of a service robot that anthropomorphic features affect the judgment of warmth but not of competence. Ascriptions of warmth have also been found to predict trust in human-machine interactions. The more warmth a technical system is ascribed, the more trustworthy it appears (Kulms & Kopp, 2018). Furthermore, a study explicitly investigating the impact of the perceived level of technical autonomy on the social perception of intelligent personal assistants (such as Amazon's Alexa and Apple's Siri) suggested that growing autonomy increases ascriptions of both warmth and competence (Hu, Lu, Pan, Gong, & Yang, 2021). In sum, these findings suggest that people tend to ascribe warmth and competence to technical systems and that increasing levels of technical autonomy may lead to more ascribed warmth and competence.

Another approach to understanding social perception centers on a more specific domain: the mind. Researchers have investigated if and under what conditions an entity is perceived as having a mind. According to this paradigm, mind perception is comprised of two dimensions: experience and agency (Gray, Gray, & Wegner, 2007; Waytz, Gray, Epley, & Wegner, 2010). While experience describes whether an entity is ascribed the capacity to sense and feel, agency indicates if an entity is ascribed the ability to plan and act (Waytz, Gray, et al., 2010). According to Gray et al. (2007) mind perception is closely interlinked with an entity's moral status: Someone (or something) perceived as having substantial agency is considered a moral agent, and as such bears moral responsibility. Inversely, entities perceived as being capable of experience are regarded as moral patients, and as such possess moral rights (Waytz, Gray, et al., 2010).

In their study of mere ascription of mind perception dimensions Gray et al. (2007) compared different entities with regards to how much and what type of mind they were ascribed. This comparison showed that human beings are attributed a considerable amount of agency and experience. An animal such as a frog is attributed little agency but much experience. In that study, participants were also asked to rate a social robot, which was ascribed a medium amount of agency and almost no experience. Thus, people tend to ascribe mind perception dimensions to technical systems. The ascription of a mind is closely interlinked with contextual factors such as the function a technical system fulfills. If a technical system primarily performs social tasks and acts as a caregiver, it is perceived as having a stronger capacity to experience (as opposed to a condition where the same system primarily performs economic tasks and acts as a salesperson) (Wang & Krumhuber, 2018). In an experiment with a self-driving car, participants ascribed more agency and experience to a vehicle that was given a name, voice, and gender, as compared to a self-driving car without these cues (Waytz, Heafner, & Epley, 2014). Additionally, (un)predictability has been found to be a determinant in ascribing a mind; the more unpredictable the entity acts, the more mindful it appears (Waytz, Gray, et al., 2010). Applied to the concept of technical autonomy, which renders actions of technical systems opaque, this suggests that an increasing level of autonomy might make the ascription of a mind more likely.

2.1. The present study

Overall, the findings reported above show that people readily ascribe to technical systems concepts and variables that are usually employed in human-human perception, such as warmth, competence, agency, and

experience. In studies concerned with mind perception, these ascriptions were found to follow a persistent pattern; technical systems were ascribed more agency (and thus the capacity to act) than experience (and thus the capacity to sense) (Gray et al., 2007; Stafford, MacDonald, Jayawardena, Wegner, & Broadbent, 2014). However, none of the studies cited above systematically tested how increasing levels of technical autonomy shape such perception. The pattern of ascription related to the universal dimensions of social cognition (i.e., warmth and competence) is less clear. Some studies indicated that technical systems were ascribed competence but not warmth (Pan et al., 2018), whereas other findings suggested that under increasing levels of technical autonomy perceived warmth and competence increased (Hu et al., 2021). In other words, the current state of knowledge on the influence of increasing autonomy on the social perception of technology is both ambiguous and fragmentary. Likewise, the notion that technical autonomy is gradual and different from automation is relatively new (see, e.g., Simmler & Frischknecht, 2021). Rather, over the past several decades, technical systems have been treated as constants (Sundar, 2020), and generally, the perception has been that a simple computer tends to elicit more or less the same social response as a sophisticated virtual assistant (see e.g., Nass & Moon, 2000; Reeves & Nass, 1996).

Thus, the goal of the present study is to further explore how increasing levels of technical autonomy generally affect such ascriptions. To do so, this research systematically explores *if* and *how* increasing levels of technical autonomy affect the social perception of a technical system. We hypothesize that the level of technical autonomy shapes how the technical system is socially perceived, and thus affects how much warmth, competence, experience, and agency it is ascribed. We further expect that the more autonomous the technical system is, the more warmth, competence, experience, and agency it will be ascribed.

To experimentally test the effect of increasing levels of autonomy on social perception, vignettes were developed for the different groups that illustrated varying levels of autonomy. To do so, the approach of Simmler and Frischknecht (2021) was employed because it provided a straightforward description of five different, consecutive levels of technical autonomy. According to their research, technical autonomy is mainly shaped by four dimensions: indetermination, non-transparency, adaptability, and openness. A technical system that is completely determined and transparent, unable to adapt to its environment, and not open (i.e., closed) is said to have no autonomy. Conversely, an indetermined, non-transparent, adaptable, and open system is considered to reach the highest level of technical autonomy. In between lie three other levels of autonomy, or what they called non-transparent, indetermined, and adaptable systems. A more detailed description of the five possible levels of technical autonomy and what technical features delineates them can be found in Table 1. It is important to note that the taxonomy represents autonomy in terms of today's possibilities, and further developments might allow for even higher levels of technical autonomy.

3. Method

This study employed a one-factorial between-subject design. Technical autonomy was the single factor and consisted of five different levels. In order to anchor the impressions of the technical system, a condition describing a human being was added. This resulted in six different experimental conditions.

3.1. Participants

All participants (N = 300) were recruited via Amazon's Mechanical Turk (m-turk). M-turk samples have been proven to be valid and of similar quality as data collected by more conventional means (Buhrmester, Kwang, & Gosling, 2011; Casler, Bickel, & Hackett, 2013; Paolacci, Chandler, & Ipeirotis, 2010). To ensure high data quality, participants were selected based on three criteria. They had to be US residents, have a Human Intelligence Task (HIT) approval rate greater

Table 1

Five Levels of Technical Autonomy and Main Characteristics (Simmler & Frischknecht, 2021)* and their Correspondence in the Vignette.

Level of Technical Autonomy	Features of Technical Autonomy	Correspondence with the Vignette
<i>Deterministic system</i>	determined, transparent, non-adaptable, closed	completely predetermined, the same input always leads to the same output, easily traceable, neither learns nor adapts, the data are specified, the system is closed
<i>Non-transparent system</i>	determined, non-transparent, non-adaptable, closed	completely predetermined, the same input always leads to the same output, <i>not easily traceable</i> , neither learns nor adapts, the data are specified, the system is closed
<i>Indetermined system</i>	indetermined, non-transparent, non-adaptable, closed	<i>not completely predetermined</i> , the same input does not necessarily lead to the same output, not easily traceable, neither learns nor adapts, the data are specified, the system is closed
<i>Adaptable system</i>	indetermined, non-transparent, adaptable, closed	<i>not completely predetermined</i> , the same input does not necessarily lead to the same output, not easily traceable, <i>able to learn and adapt</i> , the data are specified, the system is closed
<i>Open system</i>	indetermined, non-transparent, adaptable, open	<i>not completely predetermined</i> , the same input does not necessarily lead to the same output, not easily traceable, <i>able to learn and adapt</i> , the data are not specified, the system is open

*Property changes leading to higher levels of technical autonomy are marked in italics.

than 98%, and completed more than 500 HITs. Participants were paid \$1.20 for taking part in the study.

Participants were randomly assigned to one of the six conditions (consisting of the five levels of autonomy and one human control condition, see Table 1), resulting in 50 participants per condition. 12 participants had to be excluded because they failed at least one attention check. This resulted in a final sample of 288 participants (120 females, 167 males, and 1 person reporting "other" for gender). The mean age was 37.09 years (SD = 11.41).

3.2. Materials

3.2.1. Manipulation

Depending on the condition the participant was assigned, they received a description either of a technical system or human being. The descriptions were constructed based on the conception of technical autonomy provided by Simmler and Frischknecht (2021). Four technical characteristics were considered relevant for technical autonomy (i.e., transparency, determinism, adaptability, and openness; these were varied among the conditions). The structure of each description was held constant. Only the system's characteristics were modified, and the rest of the description was held as constant as possible. The key characteristics were marked in bold font (as indicated in the sample vignette below). Participants received the following vignette, with the description matching the level of technical autonomy according to the assigned condition.

The actions of the technical system are [**completely/not completely**] **predetermined**, which means that the same input

[always/not necessarily] leads to the same output. The steps to get from input to output [are/are not] easily traceable and transparent to an outsider/observer. The technical system [can neither/is able to] learn (n)or adapt to the environmental conditions in which it is embedded. The data upon which the system is based [are/are not] specified in advance. Therefore, the system is [closed/open].

Table 1 depicts the five conditions in greater detail, and illustrates how the manipulation fit the respective levels of autonomy proposed by Simmler and Frischknecht (2021). It is important to note that these descriptions were deliberately kept generic, text-based, and abstract because the goal of the experiment was to generally explore social perceptions as a function of technical autonomy. By providing a bare and abstract description of the technical system with regards to its capabilities, it is possible to isolate the effects of technical autonomy. In order to do so, appearance (Kim et al., 2018; Schroeder & Epley, 2016) and task domain (Wang & Krumhuber, 2018) had to be experimentally controlled by holding them constant, as both could have impacted participants' social perceptions. Put differently, by describing a technical system fulfilling a task such as caring for the elderly or including images or videos of a particular technical system, the effect of the technical autonomy could potentially have been confounded.

For exploratory reasons, a human (control) condition was also included in the experiment. This condition served to classify and contextualize the results. Participants in this condition received the following instruction: "Think of human beings in general. Try to imagine their capabilities and characteristics."

3.2.2. Dependent variables

All responses concerning the dependent variables were made on a 5-point Likert scale ranging from 1 (not at all) to 5 (very much). All items were presented in a randomized order to counterbalance any possible presentations effects. The survey measured four dependent variables: warmth and competence (together comprising the universal dimensions of social cognition) and experience and agency (together comprising the two dimensions of mind perception). The universal dimensions of social cognition, warmth and competence, were operationalized with the items suggested by Fiske (2018). The competence scale consisted of the following items: *competent, intelligent, skilled, efficient, assertive, and confident* (Cronbach's $\alpha = 0.84$). The warmth scale was composed of the following items: *warm, trustworthy, friendly, honest, likable, and sincere* (Cronbach's $\alpha = 0.89$). The mind perception dimensions were operationalized according to Wang and Krumhuber (2018). The agency scale consisted of the following items: *exercise self-control, think analytically, be rational, remember, and plan* (Cronbach's $\alpha = 0.87$). The experience dimension was measured with the following items: *experience emotions, have feelings, be emotional, desire, and understand others* (Cronbach's $\alpha = 0.98$).

3.2.3. Control variables

Possible covariates were also included in the survey experiment. The personal tendency to anthropomorphize served as the first control variable and was measured with the questionnaire developed by Waytz, Cacioppo, and Epley (2010) (Cronbach's $\alpha = 0.79$). The instrument contained items such as "To what extent does a cheetah experience emotions?" Controlling for the personal tendency to anthropomorphize was important, it was possible that the stronger this tendency was, the more the participant would ascribe dimensions of social cognition and mind perception variables. Technical affinity, the second control variable, was operationalized with items proposed by Franke, Wessel, and Attig (2018) (Cronbach's $\alpha = 0.82$). This included items such as "I try to understand precisely how a technical system works." Including technical affinity allowed the possible confounding effects of participants' interest in and experience with technical gadgets to be controlled, as knowledge and online self-efficacy have been found to be relevant determinants in technology perception (Araujo et al., 2020).

3.2.4. Manipulation and attention checks

In the manipulation check, participants were asked how *autonomous, independent, self-sufficient, and self-reliant* the system was according to their point of view. These items were employed in the self-developed perceived autonomy scale (Cronbach's $\alpha = 0.9$). A total of three attentions checks were built in between the dependent and control variables to identify inattentive participants. These three items took the form of directed queries (sample item: "In this row, click (undecided)"), as suggested by Abbey and Meloy (2017). The answer was considered correct if the participant clicked what was indicated in the query and incorrect if they clicked something else.

3.3. Procedure

The survey experiment was completed online and programmed on Unipark. After a general introduction, participants were provided with the following instructions on how to complete the survey: *Below, you will receive a description of a technical system and how it functions. Please read it carefully and make sure you understand the system's features. Of course, you may read the description more than once. When reading, please imagine this system in as much detail as possible.* Then the participants received a description of a technical system, depending on the condition to which they were randomly assigned. The most important features of the technical system were emphasized in bold font. In the human control condition, participants were instructed to simply rate their impressions of human beings in general. Then, participants received the following statement: *You have just read a description of a technical system. Now, you must evaluate it. Note that there is no correct answer. Simply rate the items according to your impressions.* The participants then rated their impressions regarding the universal dimensions of social cognition: competence and warmth. Next, they were instructed to read the same description of the technical system (or the human being) again and rate items related to the dimensions of mind perception: agency and experience. Then, participants were instructed to complete the manipulation check items and asked to briefly describe what kind(s) of technical system(s) they had in mind when completing the survey. The two control variables of technical affinity and personal tendency to anthropomorphize were then measured. Lastly, participants provided demographic information and were given the opportunity to provide general feedback. Finally, the participants were thanked and received a payment code.

4. Results

4.1. Preliminary analyses

All scales were found to be sufficiently reliable; therefore, all items were used for further analysis. In order to test if the manipulation worked (i.e., if the vignettes did in fact manipulate technical autonomy), a one-way analysis of variance (ANOVA) was conducted of the five levels of technical autonomy (ranging from deterministic to open systems) as factors, and the amount of perceived autonomy as a dependent variable. Because the assumption of equal variances was violated, a robust one-way ANOVA using Welch's procedure revealed a statistically significant main effect ($F(4,116.4) = 3.206, p = .015, \eta_p^2 = 0.047$). This suggests that the vignettes in fact manipulated technical autonomy.

4.2. Effects of technical autonomy

To explore the effects of technical autonomy on the general social perception of a technical system, a multivariate analysis of variance (MANOVA) was conducted of the levels of technical autonomy as independent variables and ascriptions of warmth, competence, agency, and experience as dependent variables. The group means and standard deviations can be found in Table 2. In order to check if the MANOVA was eligible, a series of Pearson's correlations were performed among all the

Table 2

Means and standard deviations of experimental conditions.

	Warmth		Competence		Experience		Agency	
	M	SD	M	SD	M	SD	M	SD
Deterministic system	2.51	0.92	3.22	0.96	1.28	0.59	2.47	1.04
Non-transparent system	2.42	0.81	3.15	0.86	1.38	0.85	2.57	0.91
Indetermined system	2.24	0.85	2.82	0.85	1.37	0.73	2.39	1.21
Adaptable system	2.29	0.81	3.16	1.05	1.34	0.70	2.96	1.06
Open system	2.51	0.88	3.41	0.90	1.40	0.63	3.20	1.01
Human	4.28	0.74	4.45	1.02	4.89	0.26	4.49	0.68

dependent variables to see if they correlated in a moderate fashion. The correlation pattern depicted in Table 3 suggests that a MANOVA was appropriate. Additionally, a Box M test was conducted and found not to be statistically significant ($M = 53.37$, $p = .11$), indicating that the covariance matrices were roughly equal among the groups. As hypothesized, the MANOVA revealed a statistically significant multivariate effect of technical autonomy, Wilk's $\lambda = 0.86$, $F(16,6703) = 2.214$, $p = .004$, $\eta_p^2 = 0.037$. This statistically significant effect persisted when including the personal tendency to anthropomorphize and technical affinity as covariates, Wilk's $\lambda = 0.86$, $F(16,697) = 2.253$, $p = .003$, $\eta_p^2 = 0.039$.

To follow up this analysis, the univariate effects of technical autonomy on every dependent variable were explored separately. The covariates remained in the model in order to further control for their effects. Before doing so, a Levene's test was run, which suggested that the assumption of homogeneity of the variances was met (smallest $p = .378$). On the one hand, these univariate analyses revealed a statistically significant main effect of technical autonomy on competence ($F(4, 231) = 2.218$, $p = .042$, $\eta_p^2 = 0.042$). Follow-up tests revealed that participants perceived the open system as significantly more competent ($M = 3.39$, $SE = 0.128$, $p = .023$) than the indetermined system ($M = 2.801$, $SE = 0.126$). Regarding the deterministic ($M = 3.19$, $SE = 0.126$), non-transparent ($M = 3.12$, $SE = 0.125$), and adaptable systems ($M = 3.22$, $SD = 0.126$), no differences were found. This is in line with the hypothesis, according to which technical autonomy has an effect on the ascription of competence. However, the assumption that the higher the level of autonomy is, the more competence is ascribed received only partial support.

Another statistically significant univariate main effect was found on agency ($F(4,231) = 6.085$, $p < .001$, $\eta_p^2 = 0.095$). Follow-up tests using the Bonferroni adjustment showed that the open system ($M = 3.20$, $SE = 0.148$) was ascribed statistically significant more agency than were the deterministic system ($M = 2.44$, $SE = 0.146$, $p = .004$), the non-transparent system ($M = 2.54$, $SE = 0.14$, $p = .017$), and the indetermined system ($M = 2.39$, $SE = 0.149$, $p = .002$). Additionally, the adaptable system ($M = 3.02$, $SE = 0.146$) was ascribed statistically significant more agency than the indetermined system ($M = 2.39$, $SE = 0.149$, $p = .031$). Thus, this is in line with the hypothesis that technical autonomy affects the ascription of agency and supports the hypothesis that the more autonomous a technical system is the more agency it is ascribed in tendency.

On the other hand, the univariate analyses showed no statistically significant main effect of technical autonomy on warmth ($F(4, 231) =$

0.697 , $p = .595$, $\eta_p^2 = 0.012$) and on experience ($F(4, 231) = 0.357$, $p = .839$, $\eta_p^2 = 0.006$), indicating that the group means did not differ in a statistically meaningful manner. Follow-up tests using the Bonferroni correction revealed no differences among any of the experimental conditions. Thus, the findings regarding the ascription of warmth and experience both were not in line with the hypotheses. For better clarity, Fig. 1 depicts the mean ascription of warmth, competence, experience, and agency across the five experimental conditions.

4.3. Contrasting technical systems with humans

As explained above, for exploratory reasons, a human control group was included in the experimental design. However, it became evident that the human control condition differed drastically (and thus statistically significantly) from the conditions capturing technical autonomy; this was true for every dependent variable and the manipulation check. Thus, the condition was excluded from the main analyses, as the experiment was designed to explore the social perception of autonomous technologies and not to compare autonomous technical systems with humans. Because the assumption for MANOVA was violated, a Kruskal Wallis Test was conducted. This test revealed, a significant effect of technical autonomy on all dependent variables (i.e. warmth, competence, agency and experience), largest $p < .001$. Additionally, follow-up tests using the Dunn-Bonferroni adjustment revealed that the human control condition differed statistically significantly from every level of technical autonomy in all dependent variables (all differences below $p < .001$). Fig. 2 further highlights the difference between the conditions.

5. Discussion

The experiment described above was designed to explore if increasing levels of technical autonomy mattered for social perception, and if so, how increasing levels of technical autonomy might shape these social perceptions. Ascription patterns were systematically tested by operationalizing technical autonomy with theoretically grounded vignettes and thus describing technical systems operating on different levels of autonomy. The results suggest that increasing levels of technical autonomy did indeed influence the social perception of the technical systems. In particular, increasing levels of technical autonomy changed the ascription of competence and agency, while ascriptions of warmth and experience did not change under conditions of increasing technical autonomy. Furthermore, the results presented above were neither due to personal tendency for anthropomorphizing nor to technical affinity, as they were experimentally controlled due to their potentially confounding effects. It is also important to note that technology, even at a high level of autonomy, was attributed significantly less warmth, competence, experience, and agency than human beings.

In a broad sense, the results suggest that increasing levels of technical autonomy affect the social perception of technology in general. The evidence presented above suggests that technical autonomy shapes how technical systems are socially perceived, and therefore is an important point to consider when investigating human-machine interactions. Past research has argued that factors such as embodiment (Hoffmann, Bock, & Rosenthal vd Pütten, 2018, pp. 370–378), voice (Waytz et al., 2014),

Table 3

Correlations among dependent variables.

	M	SD	1	2	3	4
1. Warmth	2.39	0.85	1			
2. Competence	3.15	0.94	.68	1		
3. Experience	1.35	0.70	.53	.33	1	
4. Agency	2.72	1.09	.49	.63	.39	1

* Note that the human condition was excluded from this analysis as it was not part of the MANOVA.

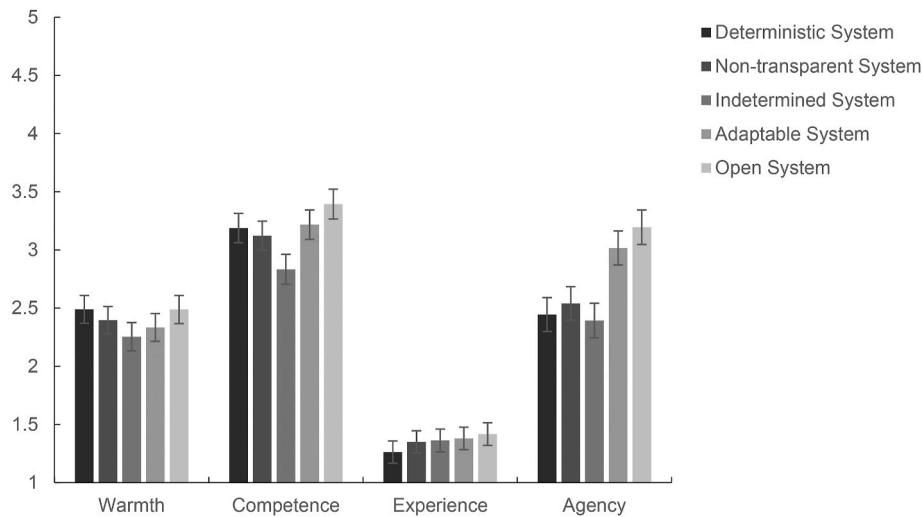


Fig. 1. Mean ascriptions of social cognition and mind perception dimensions. Mean scores adjusted for covariates, anthropomorphism, and technical affinity by condition. Error bars represent standard errors.

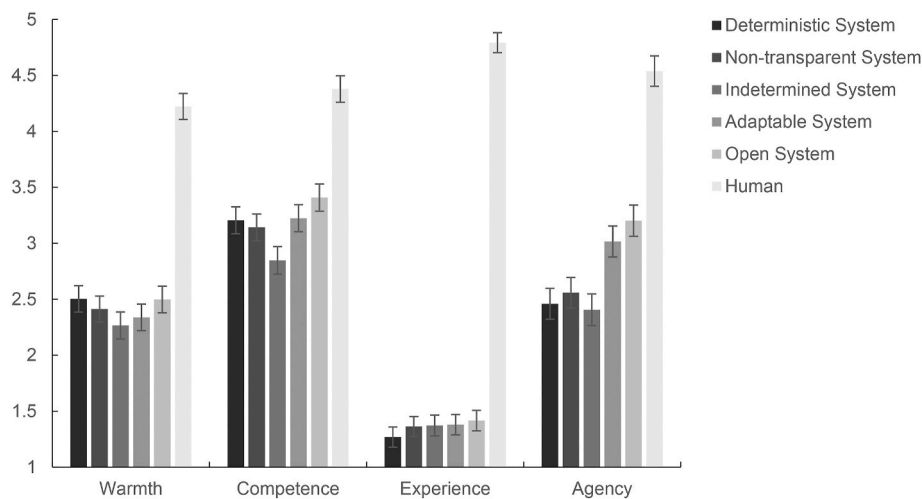


Fig. 2. Mean ascriptions of social cognition and mind perception dimensions including the human control condition. Mean scores adjusted for covariates, anthropomorphism, and technical affinity by condition, including the human control condition. Error bars represent standard errors.

gender (Eyssel & Hegel, 2012), and the social role (Wang & Krumhuber, 2018) a technical system is assigned all matter with regards to how it is socially perceived. Technical autonomy complements these findings by emphasizing that it may also be important to consider the level of autonomy at which the technical system operates.

In a narrower sense, the results also provide evidence of *how* the perception of technology is altered under conditions of increasing technical autonomy. While technical autonomy affected the ascription of competence and agency, it had no effect on ascriptions of warmth and experience. This pattern is in agreement with the results of past research on how technical agents are generally perceived: as more competent than warm as well as having more agency than experience (see for example Gray et al., 2007; Pan et al., 2018; Stafford et al., 2014).

Additionally, the data contain evidence that ascriptions of competence and agency change under conditions of increasing levels of technical autonomy. The open system and the adaptable system, both operating on relatively high levels of autonomy, were ascribed more agency than technical systems operating at lower levels of autonomy. This difference thus became evident at the level where technical systems are described as capable of learning and adapting (see Simmler & Frischknecht, 2021). The significant increase of agency ascriptions thus

might be explained by the adaptability of technical systems. Further investigating how machine learning algorithms shape social perception thus could be an interesting area for further research. Regarding the ascription of competence, a surprising pattern was observed. Although the open system was regarded as the most competent, the indetermined system was considered the least competent. According to the taxonomy of Simmler and Frischknecht (2021), this means that it was not a system operating at a low level of autonomy but one at an intermediate level of autonomy that was ascribed the least competence. The data allow no direct conclusions about why this was the case. A possible explanation for this may be that the indetermined system contains a random factor (Simmler & Frischknecht, 2021). This could have given the impression of an arbitrary or random system and thus might have had a negative impact on the ascription of competence.

Conversely, technical autonomy had no effect on the ascription of experience. Experience is closely related to having and expressing emotions (Gray et al., 2007) and thus may simply have been too far removed from what a technical system, regardless of its level of autonomy, can realistically be ascribed. Likewise, the findings indicate no effect of increasing levels of autonomy on the ascription of warmth, which is in contrast to the results of Hu et al. (2021). According to that

study, the higher the perceived autonomy of an intelligent service assistant was, the more warmth participants ascribed to it. One potential explanation of why the present study failed to replicate these findings might lie in the operationalization of technical autonomy. While this study presented generic vignettes referring to “a technical system,” Hu et al. (2021) investigated the effects of intelligent virtual assistants, and thus technical agents with anthropomorphic features such as names and voices that fulfilled social tasks and helped or assisted human beings. Past research has shown that characteristics such as a human-like appearance increases perceptions of warmth (Kim et al., 2019), and that occupying a social role determines the ascription of experience (Wang & Krumhuber, 2018). Thus, it may be that technical autonomy per se impacts the ascription of competence and agency, while bodily or contextual features such as a friendly face or social role impact the ascription of warmth and experience. Because this study does not provide a potential explanation for this, future research should explore how technical autonomy interacts with other factors. A deeper understanding of how the perception of warmth and technical autonomy relate is crucial because the perception of warmth seems to determine trust (Kulms & Kopp, 2018), and trust is highly relevant in the context of human-machine interactions (de Visser et al., 2018).

As this study's aim was to explore the impact of technical autonomy in only a general sense, no direct behavioral consequences of these ascriptions were measured. However, by matching the findings with results from past research, two possible implications become clear. First, competence and agency describe behavioral and intellectual abilities, and the results suggest that people ascribe more intellectual ability to technical systems described as operating with higher levels of technical autonomy. Because of this, people may be more likely to act on suggestions and recommendations from systems operating at higher levels of autonomy. Yet, this remains only a proposition. In their series of experiments, Logg, Minson, and Moore (2019) showed that people in fact are willing to rely on the advice of algorithms. Future research should also investigate how increasing levels of technical autonomy affect this willingness, what actual impacts (if any) increasing levels of technical autonomy have on decisions, and if people do, in fact, tend to rely more heavily on outputs produced by systems with greater levels of autonomy. Secondly, in the present research, as the autonomy level increased, more agency was attributed to the technical system. Entities described as being capable of agency are considered moral agents, which are usually regarded as being responsible for their actions (Waytz, Gray, et al., 2010). So far, it has been shown that machines are blamed less for errors than are humans (Awad et al., 2020). However, it may be that judgments regarding responsibility change under conditions of increasing technical autonomy. Whether or not advanced technology is regarded as responsible for its actions could for example have implications for future legislation.

The experiment and findings presented here have certain limitations. Two of those limitations are related to the application of generic vignettes that abstractly described technical autonomy and did not provide any further information. First, this may have been difficult to understand. However, the manipulation check showed that perceived autonomy differed across the conditions and that the relationship was linear (i.e., the higher the level of autonomy described in the vignette, the more autonomous the technical system was perceived by the participants). This suggests that the manipulation of the level of autonomy did work as intended and the vignettes were sufficiently comprehensible. Second, the generic vignettes might limit the applicability of the results in more specific contexts. The perception of technology and human reactions to it might vary by contexts (Rahwan et al., 2019). For example, Wang and Krumhuber (2018) demonstrated that a robot was ascribed more experience when it fulfilled a social role as opposed to when that same robot fulfilled an economic role. Given this context dependence of human-machine interactions, it might be that technical autonomy is perceived differently when it is implemented in a hospital rather than an investment bank. Thus, testing the effects of technical

autonomy on social ascription patterns across different social contexts would be an interesting area of further research. Another concern is related to the external validity of the results. The data were gathered via an online experiment, and thus did not allow for predictions regarding the influence of increasing levels of technical autonomy in the real world. In the real world, human-machine interactions take place in complex settings where attention is never directed to a single feature of the technology. Thus, the experiment likely overestimated the effects of technical autonomy in the real world. Lastly, due to this experiment's explorative nature, possible moderators and mediators were not considered in the design. Likewise, it was beyond this paper's scope to test associations between warmth, competence, experience and agency and how the levels of autonomy shape combinations of these perceptions.

6. Conclusion

Self-driving cars, predictive policing software, and care robots all require advanced technical capabilities such as the ability to adapt to their environment and enlarge their initial source data (Rahwan et al., 2019). As a result, these technical systems have become more autonomous. This study explored the influence of increasing levels of autonomy on how machines are socially perceived, since people tend to treat technology as a social actor (Nass & Moon, 2000). For many years, the prevailing view was that people reacted socially to technology and that functionality played little role in the response (i.e., a simple computer would elicit roughly the same social response as an advanced, adaptable recommender system) (Reeves & Nass, 1996). Technical functioning such as technical autonomy was considered a constant (Sundar, 2020) and thus regarded as negligible. Counter to this, the present work suggests that the functioning of a technology does, in fact, matter for social perception because under conditions of increasing technical autonomy, social perceptions differ and change. Technical autonomy is a relevant variable that matters in human-machine interactions.

Credit author statement

This work is single authored by Ruth Frischknecht.

Declaration of competing interest

The author declares no conflicts of interest. This research did not receive any specific grants from funding agencies in the public, commercial, or not-for-profit sectors.

References

- Abbey, J. D., & Meloy, M. G. (2017). Attention by design: Using attention checks to detect inattentive respondents and improve data quality. *Journal of Operations Management*, 53(1), 63–70.
- Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society*, 35(3), 611–623.
- Awad, E., Levine, S., Kleiman-Weiner, M., Dsouza, S., Tenenbaum, J. B., Shariff, A., et al. (2020). Drivers are blamed more than their automated cars when both make mistakes. *Nature Human Behaviour*, 4(2), 134–143.
- Banks, J. (2019). A perceived moral agency scale: Development and validation of a metric for humans and social machines. *Computers in Human Behavior*, 90, 363–371.
- Beer, J. M., Fisk, A. D., & Rogers, W. A. (2014). Toward a framework for levels of robot autonomy in human-robot interaction. *Journal of Human-Robot Interaction*, 3(2), 18.
- Broadbent, E. (2017). Interactions with robots: The truths we reveal about ourselves. In S. T. Fiske (Ed.), *Annual review of psychology* (Vol. 68, pp. 627–652).
- Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, 6(1), 3–5.
- Carpinella, C. M., Wyman, A. B., Perez, M. A., & Stroessner, S. J. (2017). The robotic social attributes scale (RoSAS): Development and validation. *Proceedings of the 2017 ACM/IEEE international conference on human-robot interaction* (pp. 254–262). Vienna, Austria: ACM.
- Casler, K., Bickel, L., & Hackett, E. (2013). Separate but equal? A comparison of participants and data gathered via amazon's MTurk, social media, and face-to-face behavioral testing. *Computers in Human Behavior*, 29(6), 2156–2160.

- Corti, K., & Gillespie, A. (2016). Co-constructing intersubjectivity with artificial conversational agents: People are more likely to initiate repairs of misunderstandings with agents represented as human. *Computers in Human Behavior*, 58, 431–442.
- Dautenhahn, K. (2007). A paradigm shift in artificial intelligence: Why social intelligence matters in the design and development of robots with human-like intelligence. In M. Lungarella, F. Iida, J. Bongard, & R. Pfeifer (Eds.), *50 Years of artificial intelligence: Essays dedicated to the 50th anniversary of artificial intelligence* (Vol. 4850, pp. 288–302).
- Dressel, J., & Farid, H. (2018). The accuracy, fairness, and limits of predicting recidivism. *Science Advances*, 4(1).
- Endsley, M. R. (2017). From here to autonomy: Lessons learned from human-automation research. *Human Factors*, 59(1), 5–27.
- Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864–886.
- van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90, 215–222.
- Eyssel, F., & Hegel, F. (2012). (S)he's got the look: Gender stereotyping of robots. *Journal of Applied Social Psychology*, 42(9), 2213–2230.
- Fiske, S. T. (2018). Stereotype content: Warmth and competence endure. *Current Directions in Psychological Science*, 27(2), 67–73.
- Fiske, S. T., Cuddy, A. J. C., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, 11(2), 77–83.
- Franke, T., Wessel, D., & Attig, C. (2018). A personal resource for technology interaction: Development and validation of the affinity for technology interaction (ATI) scale. *International Journal of Human-Computer Interaction*, 1–12.
- Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. *Science*, 315(5812).
- Hoffmann, L., Bock, N., & Rosenthal vd Pütten, A. M. (2018). The peculiarities of robot embodiment (EmCorp-Scale): Development, validation and initial test of the embodiment and corporeality of artificial agents scale. *Proceedings of the 2018 ACM/IEEE international conference on human-robot interaction* (pp. 370–378). Chicago, IL, USA: Association for Computing Machinery.
- Hoddinghaus, M., Sondern, D., & Hertel, G. (2021). The automation of leadership functions: Would people trust decision algorithms? *Computers in Human Behavior*, 116.
- Hu, Q., Lu, Y. B., Pan, Z., Gong, Y. M., & Yang, Z. L. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management*, 56, 15.
- Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260.
- Kim, S. Y., Schmitt, B. H., & Thalmann, N. M. (2019). Eliza in the uncanny valley: Anthropomorphizing consumer robots increases their perceived warmth but decreases liking. *Marketing Letters*, 30(1), 1–12.
- Kim, S., Zhang, K., & Park, D. (2018). Don't want to look dumb? The role of theories of intelligence and humanlike features in online help seeking. *Psychological Science*, 29(2), 171–180.
- Kulms, P., & Kopp, S. (2018). A social cognition perspective on human-computer trust: The effect of perceived warmth and competence on trust in decision-making with computers. *Frontiers in Digital Humanities*, 5(14).
- Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, 5(1).
- Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90–103.
- McNeese, N. J., Demir, M., Cooke, N. J., & Myers, C. (2018). Teaming with a synthetic teammate: Insights into human-autonomy teaming. *Human Factors*, 60(2), 262–273.
- Morris, K. C., Schlenoff, C., & Srinivasan, V. (2017). A remarkable resurgence of artificial intelligence and its impact on automation and autonomy. *IEEE Transactions on Automation Science and Engineering*, 14(2), 407–409.
- Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, 56(1), 81–103.
- Nass, C., Moon, Y. M., & Carney, P. (1999). Are people polite to computers? Responses to computer-based interviewing systems. *Journal of Applied Social Psychology*, 29(5), 1093–1110.
- Nass, C., Moon, Y., & Green, N. (1997). Are machines gender neutral? Gender-stereotypic responses to computers with voices. *Journal of Applied Social Psychology*, 27(10), 864–876.
- Nissen, M. E., & Sengupta, K. (2006). Incorporating software agents into supply chains: Experimental investigation with a procurement task. *MIS Quarterly*, 30(1), 145–166.
- Pan, M., Croft, E. A., & Niemeyer, G. (2018). Evaluating social perception of human-to-robot handovers using the robot social attributes scale (RoSAS). *Proceedings of the 2018 acm/ieee international conference on human-robot interaction* (pp. 443–451). Chicago, IL, USA: ACM.
- Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon mechanical Turk. *Judgment and Decision Making*, 5(5), 411–419.
- Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., et al. (2019). Machine behaviour. *Nature*, 568(7753), 477–486.
- Rammert, W. (2011). *Distributed agency and advanced technology or: How to analyse constellations of collective*. Berlin: Inter-Agency.
- Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people*. Center for the Study of Language and Information: Cambridge University Press.
- Schroeder, J., & Epley, N. (2016). Mistaking minds and machines: How speech affects dehumanization and anthropomorphism. *Journal of Experimental Psychology: General*, 145(11), 1427–1437.
- Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., et al. (2020). Machines as teammates: A research agenda on ai in team collaboration. *Information & Management*, 57(2), 103174.
- Seeber, I., Waizenegger, L., Seidel, S., Morana, S., Benbasat, I., & Lowry Paul, B. (2020). Collaborating with technology-based autonomous agents: Issues and research opportunities. *Internet Research*, 30(1), 1–18.
- Simmler, M., & Frischknecht, R. (2021). A taxonomy of human-machine collaboration: Capturing automation and technical autonomy. *AI & Society*, 36(1), 239–250.
- Stafford, R. Q., MacDonald, B. A., Jayawardena, C., Wegner, D. M., & Broadbent, E. (2014). Does the robot have a mind? Mind perception and attitudes towards robots predict use of an eldercare robot. *International Journal of Social Robotics*, 6(1), 17–32.
- Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human-AI interaction (HAI). *Journal of Computer-Mediated Communication*, 25(1), 74–88.
- de Visser, E. J., Pak, R., & Shaw, T. H. (2018). From "automation" to "autonomy": The importance of trust repair in human-machine interaction. *Ergonomics*, 61(10), 1409–1427.
- Wang, X. J., & Krumhuber, E. G. (2018). Mind perception of robots varies with their economic versus social function. *Frontiers in Psychology*, 9.
- Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human? The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science*, 5(3), 219–232.
- Waytz, A., Gray, K., Epley, N., & Wegner, D. M. (2010). Causes and consequences of mind perception. *Trends in Cognitive Sciences*, 14(8), 383–388.
- Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, 52, 113–117.
- Zlotowski, J., Proudfoot, D., Yogeewaran, K., & Bartneck, C. (2015). Anthropomorphism: Opportunities and challenges in human-robot interaction. *International Journal of Social Robotics*, 7(3), 347–360.