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Abstract: This article discusses aspects of future research in communication sciences related to a popular and omnipresent artefact of algorithmic machines, social robots. Social robots are defined in this article as physical entities or machines, which may resemble a human being or animal and are able to replicate certain human or life-like movements and functions. Experts predict that robots, just like AI, will replace a significant number of jobs in the near future, including non-industrial jobs such as robots working in offices or the service industry alongside human 'co-workers' (Brookfield Institute, 2016; Ford, 2015; Gunkel, 2018). Likewise, we may find more robots in our private lives, for example, replacing human care workers (Ishiguro, 2018; McGinn et al., 2020). Overall, the field of robotics, and particularly social robots, offers a broad range of research opportunities and exigencies for communication scientists. The aim of this conceptual paper is to provide a framework for the discussion of algorithms, social robots and communication sciences.

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Frauke Zeller

Algorithmic Machines

From Binary Communication Designs to Human-Robot Interactions

1 Introduction

It is today rarely contested that algorithms influence our lives in all dimensions – social, economic, political, legal, and cultural. Communication scholars have thus started to critically look into the role of algorithms, their functions, and how they influence our communication processes (see, for example, Andersen, 2018; Bucher, 2017; Gillespie, 2014, 2016; Kitchin, 2017; Klinger & Svensson, 2018). Similarly, there is an increasing number of publications from researchers in the STEM (Sciences, Technology, Engineering & Mathematics) fields who offer cross-disciplinary introductions and discussions of algorithms (see, for example, Christian & Griffith, 2016; Fry, 2018).

This paper discusses an applied aspect and artefact of algorithmic culture (Striphas, 2015) - that is algorithms and machines such as in Human-Robot Interaction (HRI). While there has been growing attention in media (BBC News, 2018; Fowler, 2020) as well as academia (Clerwall, 2014; Dörr, 2016; Ferrara, 2020) to so-called online robots, or bots, and how their algorithmic design can cause havoc on social media, this article focuses on ‘traditional’ robots: physical entities or machines which may resemble a human being and are able to replicate certain human movements and functions (Oxford English Dictionary). Or, using a more technical definition, a robot can also be defined as "a physically embodied artificially intelligent agent that can take actions that have effects on the physical world" (Simon, 2017).

Experts predict that robots, just like AI, will replace a significant number of jobs in the near future (Brookfield Institute, 2016; Ford, 2015; Gunkel, 2018; IFR, 2019; Spence, Westerman, & Lin, 2018). Likewise, we may find more robots in our private lives in the near future, for example, replacing human care workers (Ishiguro, 2018; McGinn, 2020). Particularly robots in our social and private lives, so called social robots, often do not come with an obvious impression of being made of inorganic hardware and algorithms. Instead, social robots tend to resemble humans or animals – at least in some basic characteristics such as having eyes, a mouth, and limbs. This means they "are designed to promote anthropomorphism and zoomorphism (the attribution of human or animal characteristics to a non-human/animal entity)" (Fraser et al., 2019, p. 62). They also aim to imitate human beings or animals in their behaviour and communication patterns (Breazeal, 2002; Zeller, 2005). Thus, based on those design decisions, one can assume that they are intended to make us forget that they are autonomous machines, operating, as any intelligent machine does, on algorithms. Arguably, the past decades' development of social robots has focused in many areas on designing and producing social robots that are "increasingly humanlike, not only in physical appearance but also in the display of human psychological, affective, and behavioral features" (Giger et al., 2019, p. 111). Among developers, one main rationale for this development is the assumption that the more humanlike a social robot is, the more it will be accepted by the human user given that the similarity of human features and behaviours facilitate the interaction (Giger et al., 2019). User acceptance is also mentioned as one of the main goals in the design of HRI (Blow et al., 2006; Breazeal, 2002).

The overall aim of this conceptual paper is to provide a framework for the discussion around algorithms, social robots and communication sciences. The aim, however, is not to argue that communication researchers should become trained in programming algorithms for social robots themselves, nor to understand or reproduce the computer science details related to algorithms. Rather, in order to understand and research the relevance and role of algorithms in social robotics, algorithms or the computational processes in general need to be seen as part of the holistic, overall ‘interaction’ design approach. Similarly, Dudek and Jenkin (2010) describe the relationship between algorithms and robots in a certain subset of robots, that is mobile robots: “Mobile robots are not only a collection of algorithms for sensing, reasoning, and moving about space, they are also physical embodiments of these algorithms and ideas that must cope with all the vagaries of the real world” (Dudek & Jenkin, 2010, p. 2). This paper will discuss the interconnectedness and interdependency by discussing the front-end and back-end[1] of social robotics, and future research avenues for communication researchers. The first part of this paper will briefly introduce social robots and algorithms. It will then explain what kind of algorithms guide robots by using the binary front-end and back-end distinction as a guiding framework, and finally provide discussions of future trends and research avenues in this field for communication researchers. Given the extent and interdisciplinary nature of the field of robotics and social robotics, and the limitations of any paper published in a special issue, this paper uses a funnel-approach: it starts by providing a wide and general introduction to the overall topic, to then gradually narrowing down when it comes to discussing future trends and research avenues.

2 Social Robots and Algorithms

2.1 Social Robots

Overall, social robots can be described as being designed to interact with humans – be it to help or support them, or as friends, lovers, etc. – and thus are required to have some form of personality and usually an anthropomorphic or zoological embodiment. This means most social robots either look like humans (or at least imitate basic human features such mouth, eyes) or animals (Breazeal, Dautenhahn, & Kanda, 2016; Fraser et al., 2019). In general, one can say that a social robot fulfils all abilities and functions of a robot according to

1 Front-end and back-end describes the classic binary distinction in machines, where the front-end depicts what the user sees and interacts with, and the back-end the technological and algorithmic design (hardware and software). See, for more detail, section 2.3 of this paper.

the ISO (International Organization for Standardization) definition[2], but does that in the context of interacting with humans in a human-centric way (see also Breazeal, Dautenhan, & Kanda, 2016).

An interesting question is whether a social robot must be able to perform a certain function as industrial robots do, for example. Breazeal, Dautenhahn and Kanda (2016) state as the main unifying function or characteristic that "social robots engage people in an interpersonal manner, communicating and coordinating their behavior with humans through verbal, nonverbal, or affective modalities" (p. 1936). One of the earlier definitions of social robots takes a more socio-centric point of view:

> Social robots are embodied agents that are part of a heterogeneous group: a society of robots or humans. They are able to recognize each other and engage in social interactions, they possess histories (perceive and interpret the world in terms of their own experience), and they explicitly communicate with and learn from each other. (Dautenhahn & Billard, 1999)

Breazeal (2003) focuses on how people perceive robots and extracts her definition from there. Her point of departure is inspired by different works, such as the media equation (Reeves & Nass, 1996), which posits that humans tend to apply social models when interacting with machines, including robots.

> Autonomous robots perceive their world, make decisions on their own, and perform coordinated actions to carry out their tasks. As with living things, their behavior is a product of its internal state as well as physical laws. Augmenting such self-directed, creature-like behavior with the ability to communicate with, cooperate with, and learn from people makes it almost impossible for one to not anthropomorphize them (i.e., attribute human or animal-like qualities). We refer to this class of autonomous robots as social robots, i.e., those that people apply a social model to in order to interact with and to understand. (Breazeal, 2003, p. 168)

Zeller (2005, pp. 99-100), based on Breazeal (2002) and Dautenhahn et al. (2002), provides an overview of the different sub-classes or degrees of 'social' in social robots, ranging from:

2 According to the ISO 8373:2012, a robot is an "actuated mechanism programmable in two or more axes (4.3) with a degree of autonomy (2.2), moving within its environment, to perform intended tasks" (https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en).

- socially evocative (robots aiming to create anthropomorphization processes in humans),
- socially communicative (robots that are capable to communicate, usually in natural language),
- socially receptive (robots that can learn from humans, from motoric functions to language/communication),
- socially cooperative/sociable (robots that have their own/personal motivations which usually include the social interaction with humans),
- socially situated (robots that can perceive their environment), and
- socially intelligent (robots with empathic ability, based on human-like cognitive structures and social competencies).

One social robot can certainly cover a range of those notions of sociability, although each single objective or social trait requires often different, complex algorithmic and technological abilities. Thus, the more social traits included, the more sophisticated and usually expensive the robot is.

Generally speaking, terminologies and even definitions around social robots can be considered as changing or 'moving' targets: For example, the term social robot used to be "applied to multi-robot systems where the dominant inspiration came from the collective behavior of insects, birds, fish such as flocking, foraging etc." (Breazeal, 2003, p. 168). In her paper, Breazeal elaborates that the term 'social' had changed "to become more strongly associated with anthropomorphic social behavior" (2003, p. 168).

The notion of embodiment, one of the core concepts in the beginnings of HRI, is also changing. Deng, Mutlu and Mataric (2019) state that "most socially interactive robots do not need to physically interact with their environments in order to perform their tasks" (p. 251), and provide a research overview of the role of physical embodiment in social robotics[3]. Similarly, we have to understand the context of the term 'autonomous' used in Breazeal's quotation above. The term then is not necessarily comparable to current connotations of 'autonomous', when, for example, referring to self-driving cars. Rather, 'autonomous' refers to the ability of a robot to process sensor-based data input and then produce or show corresponding reactions, so that it appears to be autonomous or freely choosing its behaviours. Braitenberg (1984) famously discussed in his thought experiment how easily machines (or mechanical agents) can appear to be autonomous or show emotions by simply using a sensor coupled to a motor. For example, a simple moving agent (such as, a small robot on four wheels) with a light sensor can appear to be drawn towards the sun, and thus imitate emotional, autonomous behaviour (Damiano, Dumouchel, & Lehmann, 2015; Dautenhan, 2007)[4].

The broader field within which social robots are discussed is called Human-Robot Interaction (HRI). Bartneck et al. (2020) describe HRI as a discipline, which "is related to human–computer interaction (HCI), robotics, artificial intelligence, the philosophy of technology, and design" (p. 7). They state that social robots, or rather the interaction of humans with social robots, usually represent the main perspective or objective of the field, and that those "interactions usually include physically embodied robots, and their embodiment makes them inherently different from other computing technologies" (p. 7). The authors claim that social robots can be perceived as "social actors bearing cultural meaning and having a strong impact on contemporary and future societies" (p. 7). This statement can also be connected to the close coupling of social robots and fiction or popular culture in general, where robot-like automata have been displayed and narrated even a long time before Karel Čapek coined the term 'robot' in his play R.U.R. – Rossum's Universal Robots (Onnasch & Roesler, 2020; Cohen, 1966). Overall, HRI is being described as inherently multidisciplinary, connecting scholars from a broad range of disciplines and research fields such as mechatronics, engineering,

3 The literature on embodiment in HRI is vast, and discussions highly diverse. This paper will focus on embodied social robotics. For further research in this field, see Beckerle, Castellini and Lenggenhager (2018); Breazeal and Scasselati (2002); Brooks (1999); DiSalvo and Gemperle (2003); Fischer, Lohan and Foth (2012); Foster (2019); Giger et al. (2019); Gunkel (2020); Kaplan (2008); Miller and Feil-Seifer (2017); Wainer et al. (2006).

4 Braitenberg's thought experiments have since been numerously applied in basic programming or introductory AI lectures (see, for example, Ertl, 2009).

linguistics, philosophy, psychology, design, anthropology, and communication research (Bartneck et al., 2020; see also Kanda & Ishiguro, 2013). Arguably, the communication perspective has been emphasized in the field of HRI and social robotics from the start, with early studies already posing questions such as: "What are the common social mechanisms of communication and understanding that can produce efficient, enjoyable, natural and meaningful interactions between humans and robots?" (Breazeal, Dautenhahn, & Kanda, 2016, p. 1935).

2.2 Algorithms

According to Fry, "[a]n algorithm is simply a series of logical instructions that show, from start to finish, how to accomplish a task" (Fry, 2018, page 8). While the author admits that such a broad definition would also mean that, for example, baking recipes are algorithms (see also Gunkel, 2020; Bryson, 2020), too, it also needs to be stressed that this definition represents the basic form of algorithms and does not necessarily suffice to explain algorithms used in machine learning and in neural networks. Fry (2018) distinguishes between rule-based and machine-learning algorithms. Whereas the rule-based algorithms are fully programmed by humans and can be described as "direct and unambiguous" (Fry, 2018, p. 10), the second type of algorithms is "inspired by how living creatures learn" (p. 10). In fact, machine-learning algorithms are designed to be capable of basically writing themselves, based on a given framework and with the use of large data sets that allow for trial and error-based training and learning approaches to a given problem until an optimal path is found. Thus, the human programmer is not needed to provide the whole path, nor different options (so-called IF-THEN routines, for example). These algorithms have proven to be rather useful for problems that are more vague, such as in image recognition (Fry, 2018; Gunkel, 2020). However, they are also representing a technical as well as societal challenge insofar that "if you let a machine figure out the solution for itself, the route it takes to get there often won't make a lot of sense to a human observer. The insides can be a mystery, even to the smartest of living programmers" (Fry, 2018, page 11).

Staying with the algorithmic basics, according to Fry (2018, pp. 8-9) typical tasks for digital algorithms (i.e. those implemented in computing and/or digital environments) are:

- Prioritization, i.e. making ordered lists, such as in search outputs.
- Classification, i.e. picking certain categories such as in classifying and removing inappropriate content in multimedia platforms (for example, YouTube).
- Association, i.e. finding links and relationships in data sets such as on matchmaking platforms (for example, partner search).
- Filtering, i.e. sorting and isolating what is important such as in speech recognition where algorithms need to be able to filter the noise from what is actually said.

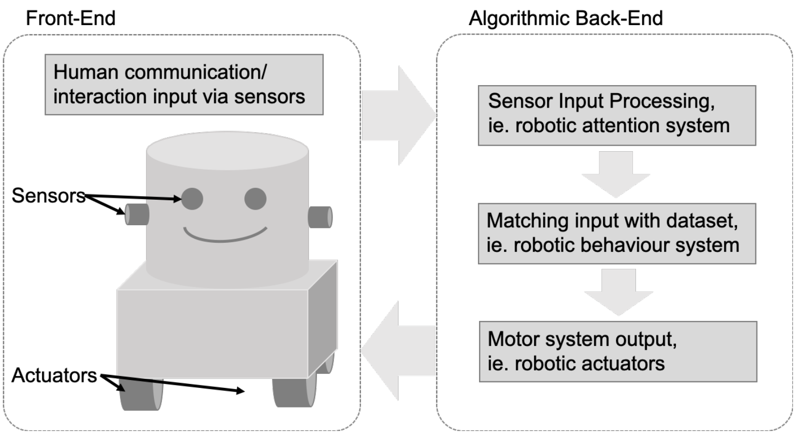
When looking at these main tasks, what comes to mind is that they are also carried out on a daily and continuous basis by humans: We need to be able to prioritize what needs to be done first when, for example, the aim is to simply have a bath (i.e. first, put the plug in the bathtub, then, run the water, etc.). We classify when we consume news or media in general, picking what is most relevant to us. Sometimes we also use association to help us here, or we associate certain experiences with new situations in order to know how to proceed. Finally, filtering needs to be performed non-stop in our communicative interactions, be it simply to filter out background noise when talking to someone in the street.

Bryson (2020, p. 6) provides a connection to the physical context or embeddedness of algorithms by stating that algorithms are first and foremost "abstractions" and, taken at face value, merely "inert" lists of instructions. Thus, other than the comparison of algorithms to baking instructions, an algorithm can be depicted as a computational procedure (Gunkel, 2020; Cormen et al., 2009). This means, physical computation is an essential part of an algorithm, no matter whether the algorithm is "intelligent" or not (see below, section 4.2): "Just as a strand of DNA in itself is not life – it has no capacity to reproduce itself – so instruction sets [algorithms] require not only input (data) but also physical computation to be run. Without significant, complex physical infrastructure to execute their instructions, both DNA and (...) algorithms are inert" (Bryson, 2020, pp. 6-7). The author's statement connects to this paper's objective, which is discussing algorithms and social robots, by emphasizing that algorithms cannot stand on their own. Rather, they are always dependent on the wider physical, computational context of a robot, and define not only the inner mechanisms and processes of a robot but also its outer reactions, interaction patterns, and abilities.

2.3 The Social Robotic Front-End and the Algorithmic Back-End

Braitenberg's (1984) thought experiment can function as an example for the classic binary distinction in machines: front-end and back-end, where the front-end depicts what the user sees and interacts with (i.e. the interface), and the back-end represents the technological and algorithmic design (hardware and software). When it comes to robots, and social or autonomous robots, the robotic system must be able to perceive its environment (or features of it) and respond to sensory input (see also Bartneck et al., 2020). The example of Braitenberg's vehicle, where a simple machine or robot moves toward the light and thus appears to the layperson to be showing a natural direct reaction, can actually be broken down into several steps or subsystems.

Figure 1. Simplified robotic front-end and back-end relational system (author's own drawing)



To demonstrate this, Figure 1 illustrates the robot interface as the front-end, including in this example two kinds of sensor input: cameras for vision (here, shown as imitated eyes on the anthropomorphized robot head) and microphones for auditory input (here, shown as imitated ears). This input is then processed in the back-end, which can also be called the robotic attention system (the term was adapted from Breazeal, 2002; and Gunkel, 2020). The processing usually contains interpreting the input (sensory input), and matching it with the internal dataset of the robot. For example, if the input is light, the dataset could contain the rule to either move towards a light source or to avoid it, and with this producing the impression that a robot either likes the light or tries to avoid it. Once the matching is successful, the machine will choose the corresponding output and activate the robot's actuators; in this case, the wheels of the robot, which produce movement. These processes are based on algorithms, which are, as depicted above, simple instructions as to what to do under certain conditions.

This simplified example shows that when it comes to planning HRI or the design of social robots, one cannot think of direct relations where a stimulus causes a straightforward reaction. Rather, a stimulus (i.e. input from a sensor) needs to be detected by the back-end, processed, and then embedded in the robotic behaviour system to finally come up with a corresponding output or reaction. Likewise, a social robot cannot function if the chosen sensor does not receive any input. Using the example of the light again, the robot will not show any reaction (ie. move towards the light) if the light source is not working, such as when the electric light fails or the sun is not visible. The fact that robotic systems are prone to malfunction given even small irregularities in their environment, deters the establishment of close relationships between humans and social robots. Following up on the light example, human users can still function when the sun is not visible or a light bulb ceases to function. Thus, in an HRI context, where a social robot's design successfully makes the user feel comfortable believing that they can interact with the robot in a similar way to the way they would interact with other human beings, those small malfunctions can trigger an uncanny valley and thus lead to a strong negative reaction on the human user side (see also Breazeal, Dautenhahn, & Kanda, 2016). Uncanny valley (Mori, 2012; Pollick, 2009) describes in robotics the effect when, for example, a robot displays some familiar humanoid features yet the arrangement or quality of these appear strange or unnatural to the user. This could be when a computer-generated voice does not match a fully anthropomorphic robot (see, for example, Hanson et al., 2005).

While Figure 1 aims to visualize the high-level functioning of a robotic system, it does not include the different extended interfaces of a robot, particularly a social robot. Zeller (2005) distinguishes four main categories of interfaces, whereas for social robots only the first three interface categories are relevant: The category *technological interfaces of a robot* mainly distinguishes between hardware- and software interfaces (as also depicted in Figure 1 as back-end). These range from interfaces between the processor and main circuit board, to algorithms that allow for the robotic hardware to work with the software. The second category is called *human-robot interface* and encompasses all components that are available for humans and robots to interact with each other. They basically range from the on/off button of a robot to computer program interfaces that allow for humans to remote control robots (these days, this is often complemented by apps that can be downloaded and installed on the user's phone). The third category, the *robot-environment interface*, can be compared to the front-end in Figure 1. Social robots need to be able to perceive their environment, at least to a certain degree, when they are intended to move around and interact (Zeller, 2005). The notion of a moving entity also expands the end-user's perception and kindles a whole set of additional interaction possibilities and expectancies (see also Breazeal, Dautenhahn, & Kanda, 2016). For example, a lot of social robots are able to follow (to a certain degree) a human user, which instils the impression of belonging together, friendship, and intelligence.

2.4 Algorithms to Imitate Human Action

Social robotics in general follows the idea of embodiment, meaning that physical robots are, on the one hand, built resembling humans so that we can learn more about humans by way of robotic experiments. On the other hand, resembling humans helps to build robots that can function in our (social) environments, that is, robots should learn from humans given that we carry out cognitive, manual, etc. tasks that are often highly complex (see, for example, Bartneck et al., 2020). Therefore, robotics and particularly social robotics apply algorithms that are based on human action analysis. This means that humans, their behaviours but also physical movements, actions, etc. represent the model social robots aim to imitate: "When a robot is doing service work or assisting humans in our daily life, it also needs to collaborate with humans and is expected to simulate human behaviors during the collaboration. For the purpose, robots are designed to understand human actions and to predict human intentions (...)" (Ji et al., 2019, p. 1). The authors differentiate between different human action categories for which algorithms are programmed so that they can study human actions and then create an algorithm-based model in order to imitate those actions. One main category is 'gestures', where particularly human hand gestures are studied via video and 3D analyses, translated into algorithms and then implemented into robots. The kind of algorithms used in these approaches utilize machine-learning, so-called deep learning algorithms. This implies that big data sets are used to arrive at possible algorithmic – and finally robotic – translations and applications. A simplified example would be the analysis of slow motion videos of manually picking up an apple and holding it. The slow motion video shows the different individual steps, including what fingers and even muscles are used, basically breaking down a gesture that might only take a few seconds into multiple screen-shots. Modern algorithms are capable to first capture those human movements, differentiate them into millions of single instances, and then translate them into technological counterparts for the robot, i.e. what sensors are used, what electronic parts are needed when and how, etc. Ji et al. (2019) thus differentiate for the analysis of human body motion multiple sub-categories, such as simple motion analysis or skeleton mapping. These are then via algorithms translated into a so-called "semantic representation", which means formal representations as in programmes and models that a machine can process, and finally result in algorithms that apply the actual interaction or action imitation (Ji et al., 2019). Overall, a multitude of research and publications on different algorithms for different aspects of robotic interactions, movements, actions, etc. exists. Many studies use humans as a model, however with varying degrees of analytic detail.[5]

5 Thomaz, Hoffman and Cakmak (2016) provide an exhaustive overview of computational, algorithmic approaches to HRI. Their meta-study complements earlier overview studies by Fong, Nourbakhsh and Dautenhahn (2003) and Breazeal, Takanishi and Kobayashi (2008) and systematically documents the different studies and approaches in computer sciences in HRI.

3 Algorithms and Communication in Social Robotics

As mentioned above (see section 2.1), communication between human users and social robots has been a pivotal topic from the start. Thus, studies looking into the different aspects of communication design including the corresponding back-end algorithmic design can be found in great numbers. Breazeal, Dautenhahn and Kanda (2016) provide an overview for social robotics research and communication, while Onnasch and Roesler (2020) include numerous exemplary studies relating to communication in HRI (see also Baron, 2015; Kanda, Shiomi, & Hagita, 2011; Sandry, 2015; Taipale & Fortunati, 2018). Thomaz, Hofmann and Cakmak's (2016) overview of computational/algorithmic approaches to HRI presents the following main areas of computational research in HRI:

- Foundational Competencies: Perceiving humans (for example, face and person recognition, gesture and pointing recognition); verbal communication (for example, generating and perceiving speech, modeling task and domain knowledge); nonverbal behaviour (for example, deictic gestures, eye gaze); affect and emotion (for example, facial expressions, recognizing human emotion);

- High-Level Competencies: Intentional action (for example, theory of mind, communicating intent); collaboration (cognitive and planning frameworks, collaborative manipulation); navigation (social models for navigation, navigation and verbal instructions); learning (characterizing human learning input, social imitation learning). (Thomaz, Hoffman, & Cakmak, 2016, p. 111)

The overview shows that most categories include communication aspects or directly point to communicative interaction features. Even features such as *navigation* include computational/algorithmic approaches to combine, for example, the navigation of a robot with verbal instructions. Zeller (2005) summarises the broad communication perspective in HRI by translating engineering and computer sciences' approaches to communication aspects in HRI into a taxonomy based on linguistics and communication research. Her taxonomy encompasses the following four main categories:

Text-based communication: A social robot's instructions, such as manuals, are one form of text-based communication. Manuals etc. are not the best communication form from a design perspective given that social robots should be designed in a way that a more natural, instinctive form of interaction is possible (Zeller, 2005). Given the analog nature of most manuals (i.e. printed) there is no algorithmic back-end either, which also underscores the break in the design logic given the algorithmic nature of a robot. Another text-based communication form is touch screens or panels for interaction. Examples are often found in service robots that, for example, are designed to help users to find their way in a hotel or to find a certain product in a warehouse (for example, Baxter, Wood, & Balpaeme, 2012; Döring et al., 2015). Touch screens using text-input often represent an additional choice of communication in order to meet different communication preferences of users.

Sound-based communication: This form of communication can range from very rudimentary sounds to signal-based functions of a robot, such as on/off, low battery level, etc. to designs that are based entirely on sound (according to Zeller, 2005). The toy robot BB8 by Sphero[6] is an example of a robot that exclusively uses different sounds (and colour signals) to communicate. Pet robots, such as the well-known SONY AIBO[7] robot dog, also use sounds like barking, yelping etc. Regarding the design of social robots, an exclusive usage of sounds does not necessarily mean that a robot is less communicative. Because we can make links to the intended living object (i.e. a dog, a baby), we are able to make up for the lack of linguistic/verbal utterances by referencing interaction with the living examples.

Visual and non-verbal communication: A commonly used communication form for social robots are color-based signals. For example, red is uniformly used for signalling a problem, such as lack of power or input/output problems. Gestures are also a form of non-verbal communication and can be found in many examples of social robots. Particularly pet robots, such as the aforementioned AIBO dog, use different movements to communicate certain feelings or behaviours. An example is here tail wagging, which signifies excitement. Another well-known robot is Kismet, developed by Breazeal (2002) at the MIT (Massachusetts Institute of Technology), which used extensive facial movements such as eye movement, eyebrows, ears and mouth to signal different moods and expressions (Zeller, 2005).

Speech-based communication: Natural language input and output represents one of the most natural communication forms between humans and social robots (Zeller, 2005; Bartnetck et al., 2020). In robotics, two different forms or sets

6 https://www.sphero.com (last retrieved 17 November 2020)
7 https://us.aibo.com (last retrieved 17 November 2020)

of abilities can be found – speech recognition and speech synthesis. A robot equipped with speech recognition is capable to perceive and 'understand' natural language input (from the human user), process it and provide adequate feedback. This feedback could be certain actions, for example when it is being told to move around, or gestures, or any other form of communication (colour/optical signals, etc.). A robot, which is also equipped with speech synthesis, can respond in natural language. In any case, one feature does not automatically trigger the other feature, or understanding language does not mean that a robot can also speak. This is because both features are very complex and require different yet collaborating algorithms and processes in the back-end.

4 Future Trends

The first sections in this paper provided general introductions to the main objects or fields of this research paper: social robots, algorithms, and communication. The following sections discuss in more detail future trends and research avenues for communication researchers in the field of social robotics and algorithms.

4.1 Socio-Economic Impact and Future Trends of Robotics

Robots have fascinated humankind for thousands of years, traceable to Greek mythology or old Egypt (see Cohen, 1966; Ichbiah, 2005; Reichardt, 1978). They have also played an almost permanent role in popular fiction, art, and the media (see, for example, Bartneck, 2004; Bartneck et al., 2020; Dautenhahn, 1998; Murphy, 2018; Pfadenhauer, 2015; Sarrica, Brondi, & Fortunati, 2019; Weiss, 2020), and there is no reason to expect that this will end soon. However, robots also elicit diverse feelings: on the one hand, robots tend to kindle curiosity and enthusiasm, or even caring instincts. On the other hand, robots have always come with a dystopian tone, challenging a strict division between 'master' and 'servant', and kindling unease that they might take over one day[8].

As a matter of fact, it is robots used in industry that, for example, 'threaten' the loss of labour carried out by humans (see, for example, Ford, 2015; West, 2018).

8 See the Golem myth, for example, in Cohen (1966).

And whereas this paper focuses on so-called social robots, recent developments in industrial production systems also call for intelligent, agile robots that can work as smart assistants together with humans: "The interaction between human and robots improves the efficiency of individual complex assembly processes, particularly when a robot serves as an intelligent assistant" (Krüger, Lien, & Verl, 2009, p. 628). This means that industrial robots also develop in the direction of intelligent collaborative robots, so-called cobots (see, for example, Akella et al., 1999; Brending et al., 2017; Bitonneau et al., 2017; Peshkin et al., 1999), a domain of research in advanced robotics (Küpper et al., 2019). As a result, Hentout et al. (2019) register that, with the development of cobots, HRI research in the context of industrial robots has significantly increased. This trend also represents a future research avenue for communication scholars, since humans and robots co-working in industrial settings and workplaces also require successful interaction and communication. From an economic point of view, industrial robots represent the biggest robotics market penetration and financial impact. According to a report by the International Federation of Robotics (IFR), the leading association for industrial robotics, robot installations in the world in 2018 amounted to 16.5 billion US Dollars, which translates into more than 420,000 installed robotic units globally. And industrial robots have been on the rise throughout the past decade: from 2013 to 2018, installations of industrial robots increased by 19% annually; with China, Japan, the United States, the Republic of Korea and Germany being cited as the main markets for industrial robots, amassing 74% of robot installations worldwide (IFR, 2019).

Boston Consulting Group (BCG) also forecasts a high growth rate for the advanced robotics market, estimating an increase of 46% of the global market value for robots in manufacturing to 18.6 billion US Dollars by 2021, and a market value for robots in logistics of three billion US Dollars (Küpper et al., 2019). Focusing again on the relationship between humans and robots, the same report predicts that advanced robotics adoption will impact the workforce in Germany, for example, to up to 43% (i.e. workers being replaced by robots), and China leading with an anticipated 67% of its current workforce replaced by robots, followed by Poland (60%), Japan (57%), and Canada (52%) (it should be noted that these statistics however fail to capture the creation of new jobs).

The IFR provides a category for non-industrial robots working alongside with and for humans – Service Robots – which encompasses different kinds of robots. Its subcategory 'Professional Service Robots' is defined as robots, "which are used outside of the home and conventional manufacturing scenarios" (Anandan, 2018, para. 5). Professional service robots encompass a range of different service segments, such as robots used for logistics-related tasks in factories and warehouses, medical robots deployed for surgeries and diagnostic tasks, or public relations robots, "which are used to provide information in shops and public spaces" (Müller, 2019). Given the overall aging populations in developed countries, medical robots' sales growth is estimated at an average around 47% annually between 2019 and 2022 (Müller, 2019). Overall, the market for professional service robots saw an increase "by 32% to US$ 9.2 billion in 2018 (over 2017)", "reaching a total of about US$ 38 billion in 2022" (Müller, 2019, para. 1, 12). Another subcategory is called 'Personal/Domestic Service Robots' and relates to robots that are designed for personal, individual interactions. Compared to the first subcategory, this one is often referred to as niche, albeit showing a great variety, too. The niche expression derives from the comparatively small market penetration, however particularly cleaning robots showed an increase of 24% in 2018 (over 2017), totaling in sales of 2.4 billion US Dollars (Müller, 2019). Market growth is estimated to strongly increase in the next three years "by an annual average of 35% [...] to just over US$ 11.5 billion in 2022" (Müller, 2019, para. 12). Given that we find personal and domestic robots often closest and most personal to us, they are also commonly referred to as social robots.

It can be expected that recent developments relating to the worldwide COVID-19 pandemic will have an impact on the socio-economic impact as well as socio-cultural role of service robots. Yang et al. (2020) are predicting more potential roles for robots in the public health sector. This is a development that already started with the 2015 Ebola outbreak, where service robots were identified for three main areas: "clinical care (e.g., telemedicine and decontamination), logistics (e.g., delivery and handling of contaminated waste), and reconnaissance (e.g., monitoring compliance with voluntary quarantines)", and the "COVID-19 outbreak has introduced a fourth area: continuity of work and maintenance of socioeconomic functions" (Yang et al., 2020). In fact, a number of academic publications have been published on the potential increase of impact and roles of service robots in sectors like travel and tourism (Kwok & Koh, 2020), geography and urban planning (Chen, Marvin, & While, 2020) or service management (Karpen & Conduit, 2020). Despite the sudden rise in interest and publications caused by the COVID-19 pandemic, the deployment of social robots – or different versions of professional service robots – cannot be expected to be a clear and linear development. Recent discussions around the physical embodiment of social robots, and whether digital versions might be just as useful (see, for example, Deng, Mutlu, & Mataric, 2019), provide an example of the changing nature of the field and the need for nimbleness and openness to emerging conditions among HRI researchers. These dynamics introduce changes in to the communication design of social robots and to the formats and contexts in which they are introduced to our daily lives.

4.2 Intelligent Social Robots

Discussions of artificial intelligence and social robotics ultimately should start with the question whether social robots can be as (or even more) intelligent as their human partners, and also include the ethical question whether they should be as intelligent.[9] It can be assumed that human users expect a social robot to be more intelligent than other robots, simply because a social robot's objective is to interact socially with humans in different contexts (Bartneck et al., 2020; Gunkel, 2020; Zeller, 2005). This does demand, in a perfect condition, a certain range of agile reaction and flexibility, which in return means a robot needs to be able to process in real time its context and respond correctly to it. Breazeal, Dautenhahn and Kanda (2016) state the long-term objectives for social robots as being "competent and capable partners for people" (p. 1935), and provide concrete demands for future social robots:

> They will need to be able to communicate naturally with people using both verbal and nonverbal signals. They will need to engage us not only on a cognitive level, but on an emotional level as well in order to provide effective social and task-related support to people. They will need a wide range of social-cognitive skills and a theory of other minds to understand human behavior, and to be intuitively understood by people. (Breazeal, Dautenhahn, & Kanda, 2016, p. 1935)

The field of HRI comprises a multitude of studies and experiments that address intelligence in social robots, such as Coronado et al. (2018) who introduce modular

9 Providing a holistic introduction to the topic AI and robotics would go beyond this paper's objective as well as any page limitations. Further reading in the field can be found here: Brooks (1999); Bryson (2018); Murphy (2019); Dubber, Pasquale and Das (2020); Wachter, Mittelstadt and Floridi (2017); Torresen (2018).

programming tools for the development of intelligent behaviour in social robots. The more engineering-related articles in this field often address discrete problems, such as related to robot vision, movement, etc., and present algorithmic solutions accompanied by context-dependent experiments with often very small sample sizes (see, for example, Phillips et al., 2018; Rosen et al., 2020)[10]. Other studies look into how people perceive intelligent social robots (see, Onnasch & Roesler, 2020, for an overview) or provide solutions for specific use cases, such as Edwards et al.'s (2018) study on AI and robots for instructional environments or studies into security and privacy issues around intelligent robots (see, for example, Ramesh, 2017).

When discussing future perspectives, the question relies on whether we are aiming to develop intelligent social robots or socially intelligent robots. The latter relates to the objective for robots to "perceive the user's needs, feelings, and intentions, and adapt to users over a broad range of cognitive abilities" (Wiese, Metta, & Wykowska, 2017, p. 1663). This led to new research coming from neurosciences and psychology, where "behavioural and physiological neuroscience methods such as motion/eye tracking, electroencephalography (EEG), […]" (p. 1663) are used in HRI studies (see also Cangelosi, 2010; Chaminade & Cheng, 2009; Cross, Hortensius, & Wykowska, 2019; Jamone et al., 2016; Mergner & Tahboub, 2009; Reuten, van Dam, & Naber, 2018; Schindler, et al., 2017; Urgen et al., 2013; Wykowska, Chaminade, & Cheng, 2016). These studies tend to show differing results given that they are often bound to small sample sizes. However, they also represent a promising new direction, where additional methods and new interaction data could enrich our understanding of HRI, including different perspectives of communication (i.e. neurological and neurocognitive-psychological insights).

Regarding the question of a social intelligent robot, Gunkel summarizes:

> [O]ne of the persistent and seemingly irresolvable issues is trying to decide whether these social artifacts do in fact possess actual social intelligence, or whether the social robot is just cleverly designed device that simulates various interpersonal effects that we […] interpret as being social, even if the device is not. (Gunkel, 2020, p. 222)

10 The broad range of academic dissemination venues in the field of robotics and intelligence provide a huge amount of potential research paths and projects. See, for example, IEEE International Conference on Autonomous and Intelligent Systems (AIS), AIAA Intelligent Systems Technical Conference, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) or AAAI conference on artificial intelligence.

Similarly, in AI, simulated intelligence versus real intelligence (weak vs. strong AI) is also discussed. As already mentioned above, algorithms can either be rule-based or use machine learning. While the scientific field of AI started with both options, the first one, also called symbol-processing approach, dominated the field of AI and the development of robots for a long time (and is therefore now called GOFAI – Good Old -Fashioned AI, see Gunkel, 2020, Dautenhahn, 2007). Gunkel (2020) describes the two inherently different approaches by citing Dreyfus and Dreyfus:

> One faction saw computers as a system for manipulating mental symbols; the other, as a medium for modeling the brain. One sought to use computers to instantiate a formal representation of the world; the other, to simulate the interactions of neurons. One took problem solving as its paradigm of intelligence; the other, learning. One utilized logic; the other, statistics. One school was the heir to the rationalist, reductionist tradition in philosophy; the other, viewed itself as idealized, holistic neuroscience. (Dreyfus & Dreyfus, 1988, pp. 15-16; cited in Gunkel, 2020, p. 69).

Regarding social robots, either approach exists. However, relating back to the future needs of social robots' abilities depicted above, and also taking into account that there will be increased interaction with social robots in our daily lives (Bartneck et al., 2020; Müller, 2019), advances in machine learning approaches, and also artificial neural networks (ANN) appear to be promising. This particularly relates to the demand for social robots to communicate naturally with human users and to interact and move freely in our homes, etc. These features appear to call for a machine learning approach, given that "[i]n general, symbolic reasoning is more appropriate for problems that require abstract reasoning, while machine learning is better for situations that require sensory perception or extracting patterns from noisy data" (Kaplan, 2016: 36). Similar to human beings, the ANN approach is based on emergent intelligent behaviour rather than preprogrammed sets of intelligently appearing behaviours. In the ANN approach, artificial neurons are represented by the individual processors in a network, which do not possess any intelligence *per se*. Rather, the synaptic connections are represented by the messages the processors exchange ("real numbers"), and "[d]ata propagated through the network produce a pattern of activations in the interconnected artificial neurons that eventually result in some output" (Gunkel, 2020, pp. 72-73). Through 'learning', the network then is "progressively adjusting the weighted connections" in the network and the "system can be adjusted or 'tuned' to exhibit different kinds of output behavior" (Gunkel, 2020, p.

73). ANN approaches are also called deep learning and are currently widely discussed in both academia and news media, often lacking expertise and precision, at least in the latter domain. This calls, too, for more research in the field, also coming from communication researchers, critically addressing these approaches as well as their public perceptions (Zeller, Wolling, & Porten-Chee, 2010; Zeller, 2020).

Whereas machine learning approaches in general are said to be promising for future improvements in HRI, one has to note that with the beginnings of the scientific field of AI in the 1950s, it was predicted that within a decade we would have strong AI, that is intelligent artificial systems. However, as Bartneck et al. (2020) state, "half a century later, AI still struggles with understanding human sentences" (p. 206). And although the impression might be supported by means of news media reporting that deep learning and ANN are new developments, their origins also go back to the 1950s. Furthermore, when comparing studies in HRI regarding human acceptance and interaction preferences with social robots, there is a "lack of comparability and generalizability", which can be attributed to the "plethora of robotic appearances and interaction concepts" (Onnasch & Roesler, 2020). This, consequently, results in the need for even more data that must to be collected, annotated and processed to become training data for ML approaches. And referring back to the socio-economic impact discussion above, even though social robots are said to develop increased market share in the future (Müller, 2019), their market penetration is still relatively small compared to industrial robots. Thus, the question remains whether it would be profitable and whether funding agencies and industry have sufficient interest to invest the funds needed to support vast data projects in AI social robotics.

4.3 Disciplinary Trends

We have seen a recent increase in the number of publications in HRI coming from scholars in media and communication studies (see, for example, Fortunati, 2018; Fortunati, Esposito, & Lugano, 2015; Guzman, 2018a; Hasse & Søndergaard, 2020; Smith & Zeller, 2017, 2018; van der Woerdt & Haselager, 2019; Zeller, 2005; Zeller et al., 2019; Zhao, 2016). Whereas technology as a medium has been studied from the start in our field, robots *per se* have been more absent in the past. Moreover, the study of communication has traditionally been defined around human interaction. As Guzman (2018b) points out, "In textbooks, communication is presented within a primarily, if not exclusively, human context, with models, theories, and examples focused on people's interactions" (p. 2). The technologies discussed in this article, however, cannot be 'reduced' anymore to a medium only. Looking into the different kinds of AI-based algorithms that bring robots 'to life' shows that we are dealing with a technology in its own right, or rather an autonomous communication entity and partner to humans. Arguably, notwithstanding the actual 'intelligence' and autonomy level of any technology, in our popular media narratives (for example, Ichbiah, 2005; Murphy, 2018), and thus to a certain degree also in our preconceptions around social robots, we already tend to believe that they fulfill the roles of independent entities and (synthetic) beings. Consequently, the study of communication (messages) and effects in HRI needs to take this preconception into account, given that it influences our communication patterns and social interactions. This has been done to a certain degree and underscored by the aforementioned new studies and their reception in the communication research community. A common skeptical remark, however, is around the question whether HRI, or a field related to it, merits the disciplinary recognition as a sub-field in communication research.

One advantage of having a focused sub-field in, as Guzman (2018b) suggests, Human-Machine Communication, is that it would enable a more focused approach for the many different communication researchers and their diverse disciplinary and methodological approaches.

Second, it is important to note the paradigm shift regarding social robots and their back-end algorithms. They evolved from the role of a communication medium or facilitator to autonomous systems, and Guzman (2018b) states: "These technologies enable a qualitatively different type of interactivity than their predecessors. To use the machine is to communicate *with* it, and the "it" is more than a tool to use" (p. 12, italics in the original). Furthermore, "communication with these technologies is often personalized. These technologies do not just talk, they talk *with us*. They know *our* name, can distinguish *our* voice, and learn *our* preferences. They enter into *our* social world as active participants through their design and use" (Zhao, 2016, as cited in Guzman, 2018b, p. 12, italics in the original).

5 Main Areas for Communication Research and Research Questions

This paper discussed the connection between algorithms, social robots and communication, by emphasizing the important and persisting role communication plays in HRI and its application to the front-end and the back-end dimensions of social robots and algorithmic machines. This article also discussed multiple potential research areas for communication researchers who are interested in social robotics and algorithms. The following section lists some concrete areas for researchers in communication sciences, focusing on algorithms and social robots as well as social robots in general.

5.1 Algorithms, Social Robots and Communication

Communication researchers can enrich the HRI field by providing the necessary connection between the front-end interaction design and the back-end algorithms for successful human-robot communication. They can provide communication models and theories that will show the different contexts of communicative interaction, and translate the main parameters into an HRI design. With a high-level understanding of the back-end algorithmic and technological design, communication researchers will be able to actively consult with the wider HRI community to make pragmatic decisions as to what features are necessary in each context for communicative interaction. Additionally, communication researchers coming from the social sciences, thus having social interactions as one of their main research objectives, bring a broad set of theories, models and methods that can be adopted in HRI given the advanced nature of AI-based social robots, for example (see, for example, Gunkel, 2012; 2020; Pentzold & Bischof, 2019; Sandry, 2015; Suchman, 2007; Taipale & Fortunati, 2018; Zhao, 2016; Zeller, 2020).

5.2 Public Perceptions and Discourses of Social Robots

Content, framing, and discourse analyses are core instruments in communication research. Thus, a relevant research question is how media innovations such as social robots, AI, autonomous systems etc. are framed in public discourse (see, for example, Fritz, 2018; Šabanović, 2014; Wolbring, 2016; Wolling, Will, & Schumann, 2011; Zeller et al., 2019). These studies can provide important input for the design of robots and HRI insofar as they can point out the main topics or concerns that need to be addressed. The fact that social robots are now often mixed with autonomous systems and AI can lead to increased or heightened levels of concern when it comes to forming trust in social robots. The public discourses mentioned in the beginning of this article show that, when it comes to robots, a whole range of concerns has gained attention in recent years, including data privacy risks and surveillance through robots, the danger of being replaced by robots in the workplace, or ethical considerations (see Spence, Westerman, & Lin, 2018; Wolbring, 2016). Arguably, these points also underscore the need for communication researchers with expertise in knowledge translation and mobilization, and an important research question in these domains is 'How can institutions, companies, etc. best communicate about social robots, AI, algorithms, etc.?' For the future design of humans and robots working collaboratively, for example, and social robots entering our homes, it is important to understand the factors that promote both respect and acceptance among users. Moreover, it is also crucial to collect feedback from the public regarding needs, research interaction patterns, emotions, and preferences, and to also look into potential dysfunctional aspects in HRI (Taddicken & Reif, 2020). Knowledge translation and mobilization aims to engage the public and to enter a fair discourse between researchers, developers, politicians and end-users (Haidegger et al., 2013; Horowitz, 2016; Smith & Zeller, 2018; Wilkinson, Bultitude, & Dawson, 2011; Zeller & Smith, 2015). Communication researchers have the instruments and knowledge to mobilize these discourses and to analyze them.

Communication researchers are also equipped to provide a taxonomy or classification of concerns, helping to disentangle the multiple discourses around social robots, intelligent algorithms, autonomous systems and the threats coming from each of these topics. Not all social robots (probably only a small proportion) use machine-learning based algorithms and employ high-end AI techniques. Nevertheless, it is difficult to differentiate the different levels of algorithms and their potential 'harms' in public discourse and popular scientific communications. Communication researchers can use their wide repertoire of quantitative and qualitative instruments to provide an overview of the different voices, opinions and topics. Furthermore, they could also follow-up with the important question as to how the public or different groups receive such messages, and what impact they have.

5.3 Communication between Humans and Social Robots

Another important area of research is to analyze the conversations between humans and social robots. One of the most prominent approaches is the application of personality traits in HRI.[11] These studies attempt to discover (a) whether personality traits in humans have an influence on engagement with robots, and (b) which personality traits in robots have a positive impact on HRI. Santamaria and Nathan-Roberts (2017) provide an exhaustive overview of this specific approach and their finding is that studies rarely look at personality traits and their influence on the communication and interaction on both sides – humans and robots. Instead, they mostly focus on robots. Also, whereas most studies use the Big-Five Personality approach, the majority of these focus exclusively on extraversion and introversion (Santamaria & Nathan-Roberts, 2017).

It is an open question whether humans address and interact with robots the same way they would communicate and interact with humans. Overall, the problem is that there is a lack of consistency of study designs and thus results. This problem has been pointed out by several researchers. According to Dautenhahn (2007), social robots tend to come in a broad variety of designs and are used in a multitude of different contexts. Thus, it is difficult to achieve replicable approaches that will also allow researchers to arrive at more consistent and representative study results. However, there is an increasing number of publications and studies that look at the communication perspective in HRI. Brandstetter and Bartneck (2017) look at the question whether robots have the potential to influence our language use, since we are often willing to adapt to a robot's communication repertoire for the sake of a successful interaction. They found that "robots owned by highly connected people [people with more social attachment] have less effect on the dynamics of language than robots owned by less connected people [people with less social attachment]" (p. 275). The results are interesting given that most studies focusing on lexical entrainment[12] in HRI (see, for example, Beckner et al., 2015; Brandstetter et al., 2017; Iio et al., 2014, see also Tangiuchi et al., 2019) are restricted to small sample sizes

11 Whereas personality traits and the Big-Five are often criticised elsewhere, in HRI they appear to dominate, as found out in a meta-study by Santamaria and Nathan-Roberts (2017). See, for example, McColl et al., 2016, for studies that use different approaches, such as affect and emotions.

12 Lexical entrainment describes the tendency of a person to change their language usage to adapt the language usage of the robot.

and also often to bilateral interaction setups, i.e. one human and one robot. Brandstetter and Bartneck (2017), on the other hand, used simulations in order to expand the standard setup and include more humans and robots, adding the variable of group behavior influence. Thus, with the rise of studies that use and/or combine communication research, linguistic, and behavioral studies[13], we can enhance significantly the number of studies that answer to important standards in terms of reliability and validity. This will enable us to arrive at more holistic, potentially representative conclusions and insights in the field of HRI.

6 Conclusion

Communication research – and neighboring disciplines such as linguistics or behavioral studies – can be seen as carrying an essential role in the research and development of social robots and/or algorithmic machines. Using the two terms – social robots and algorithmic machines – in fact also reflects the dichotomy in HRI, which has long influenced its research aims, outlooks and approaches. 'Social robots' basically stands for the 'front-end', which the user sees and (thinks) they are interacting with. 'Algorithmic machine' stands for the 'back-end', which is the hardware and software and something the user usually does not get to see. However, with the increasing critical discussions about robotics, AI, and algorithms, which are also the concern of communication researchers, the need and desire to understand more about the 'back-end' has been kindled in the user. Arguably, it has been mostly humanities and social sciences researchers that have started to critically discuss ethical and moral, but also legal, economical, and societal aspects of robotics, AI, and deep learning algorithms in the recent years (see, for example, Dubber, Pasquale, & Das, 2020; Gunkel, 2012, 2018; Lin, Abney, & Bekey, 2011). It is probably also because of those discussions that research funding agencies are

13 I am mentioning linguistics and behavioral studies here, too, since communication research in HRI and HCI often tends to be multi-disciplinary (see also Guzman, 2018) and some of the examples mentioned also use approaches and concepts from linguistics and behavioral studies.

starting to demand more interdisciplinary research and create new programs, which feature terms like 'responsible AI' in their mandate[14].

Given the rapid increase of social robots in our daily lives – from service robots in stores or hotels to toy robots in our homes – communication research needs to expand the notion of 'social interaction' to algorithmic machines that act and are accepted as independent social actors in their own right. This does not negate the fact, of course, that there will always be robots, which will be perceived more like computers or other digital devices. Nevertheless, our communication and interaction sphere has changed and will be even more challenged in the near future, such as our notion of a unified public sphere that now appears fragmented in the context of social media, for example. Similar to the development of new sub-fields in communication research, such as computational communication sciences and computational social sciences to answer the new demands of social media research, it is also time for the institutional and educational introduction of human-machine communication or Human-Autonomous Systems-Interaction (HASI[15]). Institutional in the sense that important research venues such as international conferences and associations should include sections that recognize social robots and intelligent systems in their own right. Educational means that we need the introduction of theories and applied methods for/into algorithmic machines into the communication research syllabus.

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15 Terminology suggested by the author.

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