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The growing importance of machine learning

Machine learning (ML) represents a key link to both data analytics and human–robot interaction. The Royal Society (2017) localizes machine learning at the intersection of artificial intelligence (AI), data science, and statistics, with applications in robotics. Machine learning in society is a topic of central relevance to computational social science (CSS) because it changes both the object and methods of social science. While survey research is expected to remain a supporting pillar, the collection and analysis of digital behavioral data broaden the spectrum of social research substantially. Such data involve digital marks (including user-generated content such as commentaries, blogs, posts) people leave when surfing the web. In addition, people also leave their mark beyond this narrower sphere of social media. Human behavior increasingly takes place within other digital environments and inadvertently enriches the (potential) database of social research. Current examples involve smart-home systems, interaction with intelligent voice assistants, streaming services, positioning in transit, online measurement of (psycho-)physiological parameters when doing sport, online shopping, digital payment methods, and intelligent assistant systems in motoring. In the near future, data from autonomous driving and more refined and deepened forms of human–robot interaction will be available.

In view of the expected strong international competition in the further development of AI and ML, the growing interest in this next-generation technology comes as no surprise. The economic and scientific importance will arouse a strong and continuing interest of many stakeholders in getting applications of AI and ML diffused into the population. Looking at a key element in this development, ML, its economic power is beyond all doubt. A recent forecast expects it to contribute up to 15.7 trillion USD to the global economy in 2030, "of this \$6.6 trillion is likely to come from increased productivity, and \$9.1 trillion is likely to come from consumption-side effects" (Rao & Verweij, 2017), with the biggest sector gains from AI expected in retail, financial services, and healthcare. Similar figures, indicating an exponential growth of market potential of up to nearly 90 billion USD in 2025, are reported in Jenny et al.

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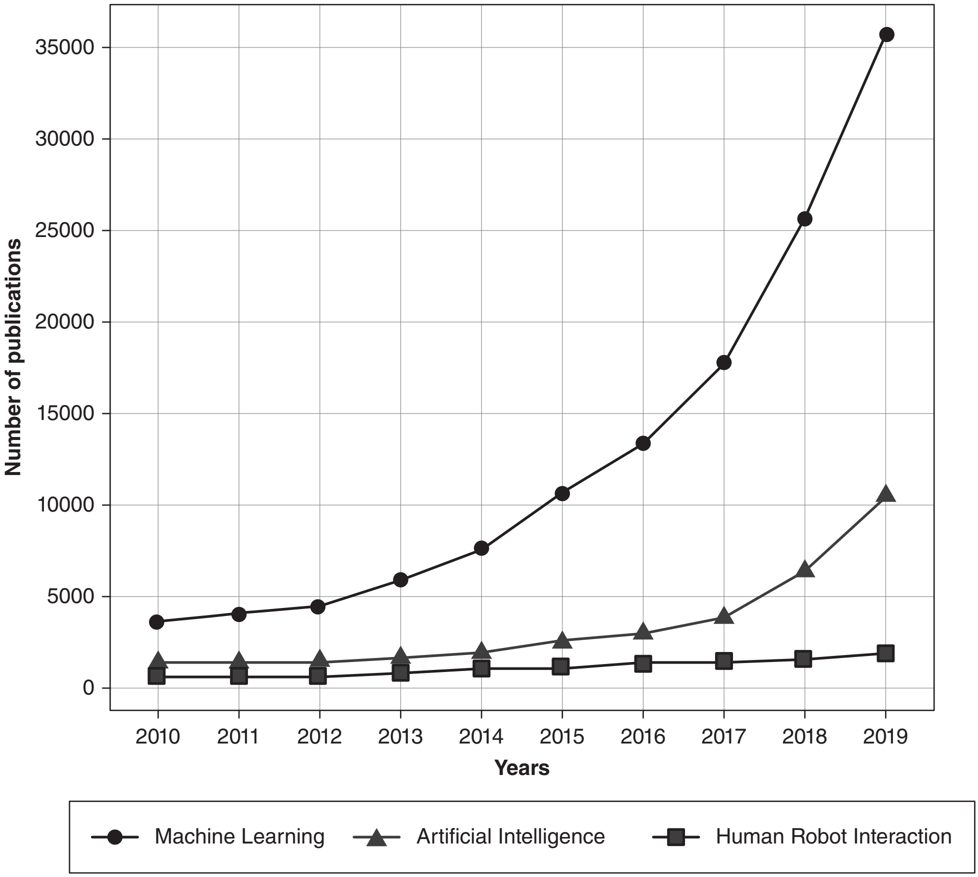

Figure 20.1 Machine learning, artificial intelligence, and human–robot interaction. Publications 2010 to 2019 (data source: web of science)

(2019). Bughin, Seong, Manyika, Chui, and Joshi (2018) assess the additional economic output due to AI on $13 trillion by 2030, boosting global GDP by about 1.2 percent a year.

In science, too, ML is a topic of exponentially growing interest (Figure 20.1). Though computer science and closely related disciplines account for the biggest proportion of publications on machine learning, social science disciplines (economics, communication science, political science, and sociology) are rapidly catching up. In part, this interest stems from the expected impact of ML-based applications on today's and future societies, but the prospect of using ML for scientific inference has gained importance (Molina & Garip, 2019). The previous market figures reveal the interest of economic researchers in the future impact of ML and AI technologies on society (Bolton, Machová, Kovacova, & Valaskova, 2018; Athey, 2018). Political scientists use machine-learning models to analyze voting behavior, the outcome of elections (Kim, Alvarez, & Ramirez, 2020), and even the detection of possible fraudulent voting behavior (Zhang, Alvarez, & Levin, 2019). As digital trace data often come in the form of textual data, for instance, tweets, blog posts, and message board entries, the growing opportunities to apply new techniques has led to a better understanding of how online communication works (Monroe, Colaresi, & Quinn, 2008; Chatterjee et al., 2019).

The digitization of society is a driving force for this research, though a coherent social-science agenda appears still developable. Data often precede the social theory needed for understanding (Radford & Joseph, 2020). ML offers enriched ways of data analytics and can also contribute to social theory in a rapidly changing, digitized world.

How will AI and robotics shape society and human life in the medium run?

Economic competition and material wealth

The growing importance of machine learning methods comes with the growing impact of artificial intelligence and robotics on human life. Particularly, the *destructive competition for permanent appointments* is a popular subject of public debate. A worst-case scenario pictures a situation that affects even the high-skilled middle class. It describes a job market where AI handles a steadily increasing part even of highly skilled routine jobs. This trend goes along with a declining demand for workforce, forcing people into precarious employment on digital crowd-working platforms and threatening even the stability of democracy. In view of the Delphi responses reported in the appendix to this chapter (Table 20.A1), this is an unlikely scenario. Though AI is expected to shape the job market in general, highly qualified staff is regarded as not that concerned, at least not for the near future. While 38 percent of the Delphi respondents anticipate a clear reduction of permanent appointments due to AI in Germany in 2030, the survey's reference year, only 20 percent believe in corresponding job losses for highly skilled academic personnel. In this respect, the prevailing expert opinion (78 percent) anticipates primarily changing job specifications due to AI.

Destructive competition for jobs is the unlikely worst-case scenario. A similarly unlikely opposite pole is a scenario based on the wealth and promise of AI. It depicts a situation in which AI has revolutionized human life, in which this technology has contributed much to the wealth of people, and in which German AI research is leading in the world. It also stresses that Germany sustained its competitive position in worldwide digitization. The Delphi respondents also rate this scenario as being unlikely overall (Table 20.A1). In relation to the involved material wealth aspect, response behavior reveals a prevalence of unlikely (41 percent) over likely (15 percent), with 44 percent of respondents voting for the mid-category "possibly".

Human–robot interaction

A third scenario describes a situation in which the social interaction of humans and robots is an expression of societal normality. In this scenario, robots belong to the daily routine of people and are involved in their communication as a matter of course. Robots are available even for personal talks in critical life situations. While the Delphi respondents regard this communication scenario primarily as becoming "possibly" a reality, they attest that the "AI assists humans" scenario is a likely perspective (Table 20.A1). For the reference year 2030, this scenario anticipates a situation in which a highly efficient and reliable AI reduces, using its assistance function, the degrees of freedom of human actions and decisions. It pictures a situation in which a multiplicity of AI-assistant systems exists and supports human action and decision-making. It insinuates that, without a human factor involved, even the most difficult tasks were now carried out more reliably, efficiently, and error free.

Such scenarios are, of course, *imagined future situations* whose relevance depends essentially on their real, later occurrence. We assume that the Delphi responses provide reasonable estimates of the anticipated probabilities of occurrence and suggest a detailed look at the various *single* dimensions that together constitute *the complex* situation of a scenario. Table 20.A2 presents a selection of such single scales to the communication and assistance scenario. One argument says that the findings unfold relevance even beyond their primarily intended scopes, fields of AI, or robot application, in fact, for social research in CSS that uses similar techniques in its future praxis.

Robots provide counseling, guidance, and consultation

If we look ten years ahead: Will then robots tend to replace humans situationally in interpersonal communication, will then specialized robots provide psychological advice (counseling), will humans then trust AI more than the humans themselves, will AI assist in rational choice (guidance), will humans seek a first doctor's advice from a robot in telemedicine (consultation)? The answer to all these questions is "probably not" if we follow the assessments in Table 20.A2 (upper segment). The expert group is quite pessimistic about robots providing required guidance, counseling, and consultation, at least by the reference year 2030. This skepticism is particularly pronounced in the case of the replacement item: it hardly appears conceivable that robots will replace humans in interpersonal communication.

Digital lifestyles

How will digital lifestyles such as the quantified self and lifelogging (Selke, 2014) evolve in the middle run? If we look ten years ahead: The Delphi respondents consider it primarily possible that lifelogging will be followed by communication of humans with personal avatars about continuously recorded life and behavioral data (Table 20.A2, middle segment). In addition, will today's digital voice assistants then have become all-embracing intelligent personal advisors, assisting humans in activities and decisions in all imaginable life situations, at home and in transit? The answer is again that it is regarded as possible that digital assistants will, in 2030, have become personal avatars as steady advisory life companions at home and en route. The same response tendency is true for the statement that "robots keep lonely people of different age company at home".

Human–robot communication

The idea of robots specialized in communication encounters obvious skepticism. Two issues contribute to this view. Interpersonal communication is genuinely human. Robots cannot replace humans that easily because they miss the human factor. A human is human; a machine is a machine. If so, even the best-qualified robots cannot simply replace humans easily in interpersonal communication. In addition, communication requires ambitious linguistic, cognitive, and emotional skills – in the context of counseling, guidance, and consultation and everyday contexts. While robots keeping *older* people company at home is rated quite probable (Table 20.A2, lower segment), more doubt resonates in robots keeping *lonely* people of *different ages* company at home (as indicated previously). Explanatory factors involve the "missing human factor" and lacking confidence in the reachability of required technical skills by the reference year 2030.

Acceptance and human–robot interaction interface to social research in CSS

Despite their obvious skepticism in the human–robot interaction (HRI) field expressed previously, the Delphi respondents expect that numerous AI assistant systems will have raised the quality of life in 2030 considerably (Table 20.A2, lower segment). This raises the question of what an increasing spread of HRI applications would imply for social research in CSS. Provided that such applications will be engineered in the near and medium-term future, their diffusion in the population(s) will depend strongly on the gain of social and ethical acceptance therein. Both are far away from being natural. In 2013, when Google aimed to launch the Google Glass, privacy advocates criticized its capability of filming people who were unaware of being filmed and the storage of data on business servers and were successful in halting the ongoing launch of the product. A likely scenario delineates societal conflict about ethical guidelines for trustworthy AI, liability rules, and ethical programming (Table 20.A1). Diffusion depends on acceptance, and acceptance depends on further factors, such as confidence in the trustworthiness of a technology and open-mindedness towards technological innovation. Social and ethical acceptance is also a key factor in survey participation, and it will become a key factor in any social research that collects digital trace data using machine-learning methods.

At first glance, HRI and social research might appear quite unrelated. However, both "acceptance" and the possibility of employing HRI applications in social research link the two fields. A case in point for a research field that lends itself to such a development is experience-sampled, real-time, and mixed self-report/sensor measurements for the study of daily life (Schwarz, 2012; Intille, 2012). Despite being affected by measurement errors due to social desirability bias and sampling bias and being costly to collect, self-reported survey data remain the most common data type. In recent years, studies based on a combination of self-reported and sensor-based data collection became increasingly popular due to the increased use of smartphones and wearables. The possibility of observing the actual behavior of participants in real time has led to substantial insights in the fields of health science (Can, Arnrich, & Ersoy, 2019; Chastin et al., 2018; Garcia-Ceja et al., 2018) and is also a promising tool for social science research. Once too expensive to equip large enough numbers of participants, sensor data have become more available for use in social research. These data prove valuable assets to differentiate between self-reported behavior and actual behavior, for example, concerning smartphone use (Jones-Jang et al., 2020) or the Internet (Araujo, Wonneberger, Neijens, & de Vreese, 2017; Revilla, Ochoa, & Loewe, 2017).

Digital trace data

Unobtrusive but not error free

Digital trace data promise the avoidance of sources of error that usually come along with survey designs. Survey interviews typically consist of series of questions and response sequences in designed interview contexts. As such, a response to a survey question reflects not only the response *to its subject*. It also reflects the way the question is worded; if an open, closed, or hybrid response format is used; which specific response format is used; if an interviewer mediates the question–response sequences; the order in which these sequences are presented to the respondent; if an interview is conducted in person, over the phone, or self-administered on the Internet; and even more. Beyond the core response to the subject of a survey question itself, further sources of response variation thus involve question wordings, mode and response effects, interviewer effects, social-desirability effects, and the possibility of motivated misreporting. Not least, the awareness of being part or even subject of research is regarded as an influencing factor. This all is well known and confirmed by numerous studies from survey methodology (e.g., Tourangeau, Rips, & Rasinski, 2000; Weisberg, 2009; Engel, Bartsch, Schnabel, & Vehre, 2012).

Consider specifically the case of motivated misreporting (Tourangeau, Kreuter, & Eckman, 2015): If the subject is some inquired behavior, it is fully comprehensible that direct observation of this behavior might be preferable over an error-prone account of this behavior given in a survey interview. It is even better if this observation remains unnoticed by the observed persons, because this rules out any behavioral reaction to being observed from the outset. If someone does not know that s(he) is part/subject of research, s(he) cannot react to such an insight – and hence no research reactivity can emerge from such an insight. Because human behavior increasingly takes place in digital environments (social media and beyond), observation of behavior is frequently transformed to *digital* observation in either of two basic forms: the observation of user-generated content (text data) and observation of the marks people leave when using the Internet (metadata). Both these textual data and the metadata represent digitally observed *behavioral* traces if the generation of content is regarded as a model of behavior, and the generated content is left in the digital space. That others take notice of ("observe") this content afterward may then be intended by the author, may occur inadvertently, or may even be unwanted. In any of these cases, it would be misleading to assume that this new class of data is error-free only because it is not obtained in conscious response to a research inquiry. Error-free digital trace data vs. error-prone survey data insinuates an incorrect contrast. Instead, digital trace data are by no means error free simply because they are collected in an "unobtrusive" (Webb et al., 1966 [2000]) manner. Sources of error exist in such data, too, and include the error we would like to pay special attention to: the systematic protection against tracking on the Internet. In studying variation in the use of shielding techniques, we study implicit variation in the acceptance of special machine-learning uses in society.

Do guarding techniques against tracking on the Internet impair digital data quality?

Web surfers can guard themselves increasingly easily against tracking on the Internet using standard built-in, privacy-enhancing modern browsers such as Firefox and Chrome; browser add-ons; virtual private networks (VPNs); and the Onion Router (Tor). Another way of protecting privacy is careful and deliberate surfing behavior, such as avoiding websites surfers deem doubtful and by refusing to give consent to cookies. Previous research points to Internet users being generally aware of the economic profits being generated with their data and therefore assessing their personal risk related to their use of online services (Gerber, Reinheimer, & Volkamer, 2019). Modern web browsers include the technical ability to restrict the traces users leave behind while browsing; browser-based privacy-enhancing technologies are often explicitly advertised as a feature of the given product (Google Chrome, 2020). After the initial installation, the user may even be reminded to select privacy preferences to protect themselves from tracking (Google Chrome, 2020; Apple, 2020; Mozilla Foundation, 2020). It is safe to say that the statement about caring about the users' safety has become a marked advantage of its own, and the user's choice of a browser directly affects the privacy experience (Al Fannah & Li, 2017).

If people guard themselves against tracking by any means, does this impair the data quality of digital trace data? Maybe only negligible random variation is emerging from such shielding behavior, in the end producing only not-biasing random noise in the data. Maybe the alternative assumption of systematic bias proves true. Then the question is, what are the relevant sources of variation? In the following, we consider the acceptance of new technology as a core element rooted in individuals' self-images and lifestyle preferences.

Current state of research on privacy and privacy-enhancing technologies

Following the rise of the world wide web, research on Internet users' privacy concerns emerged in the early 2000s. Prior studies (Mathur, Vitak, Narayanan, & Chetty, 2018; Gerber et al., 2019) on the usage of privacy-enhancing technologies points to users and non-users being generally aware of the basic mechanisms of online tracking. However, the coherence between this basic knowledge, resulting in changes in the users' behavior, and finally, the actual application of one or even multiple methods of protecting privacy still needs further research. The topic of data privacy in general or the use of privacy-enhancing technologies especially is often focused either on technical aspects or in relation to specific groups, for example, users of a specific social network such as Facebook (Van Schaik, 2018; Hargittai, 2015). In the past, studies in the field of computational social science focused heavily on digital trace data obtained in such social network settings, often using non-random samples that led to valuable findings about how and what people communicate in specific online scenarios (Hargittai, 2015; Liu, Yao, Yang, & Tu, 2017), but the lack of generalizability of the results prevails. Attitudes towards data privacy can be assumed to be culturally specific (Trepte et al., 2017; Potoglou, Dunkerley, Patil, & Robinson, 2017). Therefore, further research is needed to draw a comprehensive picture of how different cultures influence the users' requests for the implementation of data privacy guidelines. Previous findings of users' application of privacy-enhancing technologies often either focus strongly on the technical mechanisms from a computer science point of view or examine peoples' attitudes and behaviors from the perspective of the social sciences. Though plenty of findings (Spiekermann, Acquisti, Böhme, & Hui, 2015; Potoglou et al., 2017; Trepte et al., 2017) suggest the importance of addressing peoples' privacy concerns, the implications of people reacting to perceived threats accruing from their online behavior and the resulting influence on the quality of digital trace data are not yet sufficiently discussed. While the problems arising from unit-nonresponse have been in the focus of survey methodologists for a long time, methodological concerns from the perspective of researchers' aiming at the use of digital trace data are still developing (Olteanu, Kıcıman, & Castillo, 2018). The integration of survey data and digital trace data seems promising, but a potential pitfall is the possible bias of the survey data (Stier, Breuer, Siegers, & Thorson, 2020; Jürgens, Stark, & Magin, 2020).

Accepting new technology: AI-driven advice, robots in human life, and protection from tracking

"Quantified Self" designates a self-tracking lifestyle that uses digital technologies. It is directed toward self-improvement and consists of regularly monitoring and recording, often measuring elements of one's behavior or bodily functions (Lupton, 2016). It is a data-driven lifestyle that replaces the vagaries of intuition with more reliable evidence. "Once you know the facts, you can live by them" (Lupton, 2016). Self-tracking may involve target publicity and, that way, approach a competitive lifestyle through which individuals seek social recognition. Sociology knows different facets of how individuals compete for social recognition, for instance, via the acquisition of occupational prestige, even though private life is by no means less meaningful in this respect. Think of Veblen's (1899/2005) famous "conspicuous consumption" and the competitive field of fashion. Fashion means couture, and fashion means other products as well, for instance, technical equipment. Being among the first who try new technology is a case in point for acquiring prestige through a competitive lifestyle element beyond the narrower occupational sphere. A self-image of being open-minded toward digital innovation is likely to accompany the involvement in this field of competition. Rogers (2003) coined the terms innovator and early adopter to refer to individuals who want to be among the first to explore new technological innovations.

In the case of machine learning and social robots, exactly such early adopters of respective services are likely to contribute much to the acceptance of corresponding and, in part, already upcoming applications, such as assistant robots for elderly care. This acceptance is likely to be crucial because current experiences of human–robot communication may be evaluated critically, for instance, chatbots in customer service and, first and foremost, social bots flooding social networks and shaping opinion-forming processes and political propaganda.

Privacy is of utmost importance to many people. Implementing the General Data Protection Regulation (GDPR) in 2018 is likely to have contributed to an increased awareness of privacy risks when using websites, social networks, and online services. However, even if privacy ranks high, other threats to personal life may also rank highly. To date, little is known about how personal privacy concerns result in protection behavior against tracking if set in a comparative context.

The question is if people treat privacy as an isolated issue or if they embed privacy evaluations in a comparative risk perspective. Such a perspective is suggested by a theory that regards risk perception as a function of sociopolitical worldviews and lifestyles (Wildavsky & Dake, 1990). The working hypothesis states that people choose what and why to fear in line with such basic orientations. Someone may accordingly fear a possible economic downturn in Europe more than crime; someone else may fear political extremism more than abuse/trade of personal data on the Internet; yet others may fear digitization and artificial intelligence more than, for example, Brexit; and still others may fear climate change more than everything else, in this spirit. Rank order at the individual, not aggregate, level is decisive if one tries to understand related behavior. Then, it is of utmost importance to understand that the evaluation of risks implies an emotional dimension. The technical term "risk perception" involves much more than a purely perceptual component. It implies both cognitive and evaluative components and, with respect to the latter component, also possible feelings of risk (Slovic, 2010). In the present case, such feelings relate to ease with several anticipated scenarios of HRI.

Bremen AI Delphi study

A large Delphi survey of scientists and politicians in the Bremen area (Germany) was conducted to let scientists and politicians evaluate several HRI scenarios in and outside social media. These scenarios were delineated previously.

The Delphi technique was developed to obtain forecasts based on panels of experts (Linstone & Turoff, 2011). Core features of Delphi studies involve their administration in rounds (each member of an expert group is interviewed repeatedly) and the disclosure of *statistical results* from previous rounds. Participants have the opportunity to adjust their answers successively while taking notice of the respective overall picture of answers (i.e., of [parameters of] their respective frequency distribution), ideally until a consensus is achieved or until a predefined number of rounds is reached. Originally the conduct of Delphi surveys was very time consuming due to the necessity of preparing the intermediate statistical results for the successive interview rounds. Currently, Delphi studies are conducted online, sometimes even in social networks (Haynes & Shelton, 2018). In doing so, the web survey mode offers the beneficial programmable option of integrating two rounds in each interview. This works in *real time*: a first assessment is followed by presenting each respondent with the frequency distribution *of* *all first assessments* and an immediate follow-up question for reassessing the initial answer in the light of this intermediate statistical result. In the present study, this option is used for assessing and reassessing the expected probability of occurrence of the Delphi scenarios reported on previously.

A population survey about the social and ethical acceptance of artificial intelligence and social robots accompanies this Delphi survey. Findings are covered in the following. Respondents were asked in detail about their images of robots and their attitudes towards AI and some fields of AI application. They were also asked about their readiness for using AI applications, for instance, in the context of elderly care. Related to the Delphi, respondents were asked how comfortable they felt with the anticipated scenarios of HRI. Further topics involve trustworthy AI, risk perception and protection against tracking on the Internet, technical innovation, and self-image. Study details are given in the appendix of this chapter.

Findings from the population survey

Attitudes towards robots and AI

Three pillars form the structure of attitudes toward robots and artificial intelligence: the perceived necessity and goodness of this technology for society, its technical reliability, and the integrity of its application. In short, the analysis confirms the perceived necessity of robots/AI and questions its reliability and integrity at the same time. Even though mean values tightly below the upper-scale end of "quite certain" reveal a clearly positive image of robots and AI, the technology is at best acknowledged as being "possibly" safe for humans. Even more skepticism becomes apparent in the evaluation of its reliability (being error free) and its trustworthiness. In this regard, the mean values range in the middle of "probably not" and "possibly" (Table 20.A3). We observe both a high degree of basic acceptance of robots/AI in society and much scope to maximize this potential.

The latent correlations displayed in Table 20.1 indicate the expected structure among the three attitudes: the more pronounced one attitude is, the more pronounced the other. This is the expected result. While the pertaining factor loadings (Table 20.A3) point to an acceptable convergent validity of the assumed structure of attitudes, the factor correlations displayed here indicate at the same time an acceptable degree of discriminant validity: the factor correlations are substantially high, though not too high to question the involved assumption of three *distinct* attitudes toward robots and AI. Beyond that internal structure, all three attitudes correlate with the imagination of how one would feel in a series of fictitious situations of HRI. Table 20.A4 lists the eight situations whose evaluation underlies this emotional factor. Table 20.1 shows that the more respondents feel at ease with the imagination of these HRI scenarios, the more robots and AI are regarded as good for society, safe for humans, and trustfully deployed.

Most remarkable is, in turn, the high relevance of this emotional component for the anticipated use of AI-driven advice. If people condition their decisions on the anticipated consequences these are expected to educe, AI may assist in evaluating these possible consequences, thereby helping to arrive at the best possible decisions. However, how likely is it that people will apply corresponding smartphone apps in the future? From today's point of view, respondents do rate this by trend as "probably not", as the mean values in Table 20.A3 indicate. However, the more they feel at ease with imagining situations of HRI, the more they would be inclined to use such AI-driven equipment. Table 20.1 shows that both factors yield comparably the highest correlation in exactly that case.

Table 20.1 Latent factor correlations among attitudes and feelings towards robots and AI, the self-image as a person being open-minded to technological innovation, and the anticipated use of AI-driven advice

	AI is good for society	*AI is safe for humans*	*AI is trustfully deployed*	*Feel at ease with the use of*	*Would seek AI-driven advice*
AI is safe for humans	0.79				
AI is trustfully deployed	0.57	0.45			
Feel at ease with the anticipated use of	0.66	0.59	0.48		
Would seek AI-driven advice	0.56	0.50	0.27	0.66	
Self-image: Open-minded person	0.53	0.38	0.21	0.62	0.31

Confirmatory factor analysis (CFA) is detailed in the appendix to this chapter, Tables 20.A3 and 20.A4.

Comparative risk perception

Respondents were asked to rank the 5 potential risks they worry about most from the list of 14 potential risks presented in Table 20.2. Because there exist $w = G!/(G-g)!$ ways in which g objects can be selected from a group of G objects, the a priori probability *of each such individual selection* is only $p = 1/240{,}240 = 4.16 \times 10^{-6}$. This probability is vanishingly small, virtually zero, and indicates the occurrence of a single sequence we would have to expect by chance. In sufficiently large samples (with $n \geq w$), this figure could be used as a benchmark to evaluate *observed* ps of sequences. Here, this probability is a background clue that may help assess the quite even distribution of observed risk sequences: 216 trials yielded 132 different sequences of TOP 5 risks, of which 90 sequences occurred just once, 18 twice, 13 triply, 9 four times, 1 five times, and 1 eight times.

An alternative approach disregards the order in which any of the g objects became elements of an individual selection. Then the number of ways in which subsets of g objects can be formed from sets of G objects reduces to

$$c = \binom{G}{g} = \frac{G!}{g! \times (G-g)!}$$

combinations, here to $c = 2002$ possible subsets and an *a priori* probability of each such subset of $p = 1/2002 = 5.0 \times 10^{-4}$. This, again, is a tiny figure. It indicates the occurrence of a combination (subset) of the TOP 5 risks in repeated trials we would have to expect by chance. In the case of $n \geq c$, this figure could be used for benchmarking the ps of observed combinations. The present sample size is a limiting factor, however, because it truncates the lower limit of the scale of observable proportions at a point *above this* theoretical figure, namely at 1/216 = 0.0046. We limit ourselves thus to computing only the proportion that a given potential risk is part of the TOP 5 risk set of a respondent (Table 20.2). Particularly striking is the top priority given to climate change, political extremism, and hate on the Internet, while abuse/trade of personal data ranks clearly lower, and digitization and artificial intelligence is rarely part of any respondent's TOP 5 risk set.

Assuming no causality, if we would know the attitudes and feelings towards robots and AI of a person and if we would know that person's self-image, would it be possible to predict *on*

Table 20.2 Fourteen risks in comparative perspective

	Proportion (element is part of TOP 5 risk set)
Climate change	0.6713
Political extremism/assaults	0.6574
Intolerance/hate on the Internet	0.5926
Abuse/trade of personal data on the Internet	0.3796
Crime	0.3750
Migration/refugee issue	0.2917
War in the Middle East	0.2639
Possible economic downturn in Europe	0.2454
Interest policy of European Central Bank (ECB)	0.1806
Trade dispute with USA/between USA and China	0.1620
5G mobile service standard of Chinese Huawei corporation	0.1620
Digitization/artificial intelligence	0.1111
Great Britain's step out of European Union ("Brexit")	0.0926
Other	0.0370

this basis the current risk perception of that person? The answer is "yes", though the prediction would have limited predictive power only (pseudo-R^2 = 0.057). If the analysis is targeted on the odds that "abuse/trade of personal data on the Internet" is part of the TOP 5 set of perceived risks, a binary logistic regression analysis reveals notably three relevant predictors out of the set of variables from the CFA reported previously. Considering standardized coefficients $e^{b \times s(x)}$ (if $p < 0.05$), the reference odds of 0.69 change by a factor of 1.7 per standard deviation change in the belief that AI is trustfully deployed. This finding appears contradictory at first glance because it indicates that the strength of this belief *increases* the odds of perceiving the data-abuse risk instead of decreasing it. The same applies to the finding that these odds change by a factor of 1.9 per standard deviation change in the self-image of a person as someone who is open-minded to technological innovation. Here, too, one might expect a multiplying factor below the benchmark of 1.0. However, we possibly observe here two sensitizing effects *that make people more aware of* the data-abuse risk in society. Finally, aforesaid odds change by a factor of 0.4 per standard deviation change in feeling at ease with the scenarios of HRI described in Table 20.A4. The odds that "abuse/trade of personal data on the Internet" is part of the TOP 5 set of perceived risks thus appears associated with the discomfort that imagining possible scenarios of HRI conveys to people. This emotionally colored imagination of what might happen in the future is even more effective in relation to another risk. If the analysis is targeted on the odds that "digitization/artificial intelligence" is part of the TOP 5 set of perceived risks, these odds are decreased by a factor of 0.4 per standard deviation change in feeling at ease with the scenarios of HRI (considering again $e^{b \times s(x)}$ if $p < 0.05$: 0.090×0.4; pseudo-R^2 = 0.107).

Protection against tracking on the Internet

Do attitudes and feelings toward robots/AI and AI-driven advice have predictive power for the way people protect themselves from being tracked on the Internet? Table 20.3 reveals a differential picture in this regard. The use of technical means can be predicted comparably well.

Table 20.3 Odds of technical and behavioral forms of protection against tracking on the Internet and their expected change per standard deviation change in particular predictor variables

	PCA F1			*PCA F2*	
Target variables *Predictor variables*	*VPN*	*BROWSER ADD-ON*	*COOKIES*	*TRUST WORTHY*	*INFO*
Reference odds (intercept)	0.27	1.70	0.27	1.71	1.88
Would seek AI-driven advice (factor scores)	0.25	0.54			
Feel at ease with anticipated scenarios of human–robot interaction (factor scores)	4.09	1.97	0.54	0.5	
Abuse/trade of personal data on the Internet is part of the TOP 5 set of perceived risks	1.82		1.74		
Degree of belief: during surfing the web, automatically incurring use data are protected against abuse (5-point scale)	0.56	0.63			
5G mobile service standard of Chinese Huawei Corporation is part of the TOP 5 set of perceived risks		0.64			1.71
Self-image: Open-minded person (factor scores)			2.1	1.53	
AI is safe for humans (factor scores)					0.53
Pseudo-R^2 (McFadden)	0.158	0.088	0.118	0.043	0.082
Target behavior is observed (in percent):	17.8%	35.1%	31.7%	63.6%	67.8%

Binary logistic regression equations estimated using weighted sample data. Column by column is displayed: $e^{b \times s(x)}$ (if $p \leq 0.05$). Target variables: *VPN* Use of Virtual Private Networks; *BROWSER ADD-ON* Use of special browser add-ons that impede tracking; *COOKIES* Do not accept cookies when visiting web sites; *TRUSTWORTHY* Visit only web sites believed to be trustworthy; *INFO* Do preferably reveal no information on the Internet. Two-step procedure: first, all six scales (latent factor scores) from previous CFA analysis plus three comparative risk-perception indicators (abuse/trade of personal data, Huawei's 5G standard, digitization/AI is part of the TOP 5 risk set, respectively) plus the previous degree of belief in one's web-surfing data being protected against abuse) were used as the respective set of predictor variables. Second, each equation is then re-estimated, including only the statistically significant estimates of effect from step 1. A related principal component analysis reveals that VPN and BROWSER ADD-ON form a first component, TRUSTWORTHY and INFO another, with COOKIES loading on both components (PCA Oblimin-rotated, factors practically uncorrelated: −0.01). The standardization rule follows Long & Freese, 2006, p. 178.

The odds of applying VPNs, for instance, are modified by a series of statistically significant multipliers:

$$Odds\left(VPN\right) = 0.27 \times 0.25 \times 4.09 \times 1.82 \times 0.56$$

Using 1.0 again as a benchmark for an assessment, the equation shows that the odds of applying VPNs become 0.25 times smaller per standard deviation change in the vision of seeking AI-driven advice in the future. Similarly, the odds of using relevant browser add-ons produce the same change in the vision of seeking AI-driven advice, thereby pointing to some personal lack of concern with the tracking topic and thus the need to protect oneself against this practice by technical means. At the same time, the vision of seeking AI-driven advice leaves protection by behavioral means unaffected.

An influential factor is if people feel at ease with the anticipated scenarios of human robot interaction. Table 20.3 shows that the odds of applying VPNs become 4.09 times larger per standard deviation change in the felt comfort with such scenarios. While the use of relevant browser add-ons is similarly affected in relation to cookies and trustworthiness, "felt comfort" with these scenarios takes effect in the opposite direction. It lets people rely more on technical than behavioral means.

Risk perception turns out to be a relevant predictor, especially for the use of technical means. For instance, if abuse/trade of personal data on the Internet is part of the personal TOP 5 risk set, then the odds of using VPNs are expected to become 1.82 times larger per standard deviation. Equivalently, the odds are estimated to be 0.56 times smaller per standard deviation change in the belief that one's Internet use data are protected against abuse. A similar prediction concerns the odds of using relevant browser add-ons. Regarding mobile phone usage, if the 5G standard in question is part of the TOP 5 risk set, respondents tend particularly to a behavioral means, in fact, the abdication of revealing information. Finally, two effects are noteworthy: A person's self-image as being open-minded toward technological innovation favors behavioral means of guarding against tracking (only visiting trustworthy web sites, not accepting cookies), while the belief that AI is safe for humans decreases the odds of revealing no information on the Internet.

Concluding remarks

Digital trace data promise the avoidance of sources of error that usually accompany survey designs (particularly survey mode and response effects and motivated misreporting). However, error-free behavioral trace data vs. error-prone survey data insinuates a wrong contrast. Digital trace data are by no means error free only because such data are collected in an "unobtrusive" (Webb et al., 1966 [2000]) manner. The analysis has drawn attention to just one such source of error, the potentially distorting effect due to a systematic protection against tracking on the Internet. In doing so, the analysis revealed systematic variation in the use of both technical and behavioral shielding practices, most notably variation due to (a) the felt ease with anticipated HRI scenarios along with some related attitudes towards robots and AI, (b) a respondent's comparative risk perception, and (c) the self-image as a person who is open-minded toward technical innovation. In studying variation in the use of shielding practices, we implicitly also studied variation in the acceptance of special machine-learning usages in society.

Appendix
THE BREMEN AI DELPHI STUDY

Standard scale applied throughout the Delphi and the population survey

Comparable responses were ensured by a scale consistently employed throughout the two involved surveys, the Delphi and the population survey. Following recommended practice (Schnell, 2012), this standard scale rates the degree of belief in the validity of statements using an ordinal scale that ranges from 1 = "not at all", 2 = "probably not", 3 = "possibly", and 4 = "quite probable", to 5 = "quite certain". Representing these categories by their dedicated figures 1, . . ., 5, interpolated quartiles were computed for each such frequency distribution. Throughout this chapter, this is the first (Q_1), second (Q_2), and third (Q_3) quartile to obtain that way a suitable mean estimate (Q_2 = median) and the corners of the interquartile range of the 50 percent middle responses. In addition, the ordinal scale level in the confirmatory factor analyses is considered by specifying probit regressions.

Delphi survey of scientists and stakeholders

Selection frame and selection procedure

Sample design: We invited 1826 experts from two different backgrounds to participate in the Bremen AI Delphi Study, namely 1359 members of Bremen's scientific community and a diverse group of 467 people of Bremen's political landscape. The expert group of the Bremen scientific community included scientists affiliated with one of Bremen's public or private universities at the time of the survey. The prerequisite for participation was holding a doctorate or a professorship. Institutions included the University of Bremen, the City University of Applied Science, the Jacobs University Bremen, the University of Applied Sciences Bremerhaven, the Apollon University of Applied Science, the Bremen School of Public Administration, and institutes affiliated with those. Disciplines selected from social sciences included economics, sociology, political science, health science/public health, cultural science, pedagogy, media and communication science, linguistics, psychology, philosophy, and history. The field of STEM disciplines was represented by professionals in engineering, mathematics, robotics, and computer science.

Natural sciences included physics, chemistry, biology, and earth science. The group of experts of politics/officials/stakeholders included members of the Bremen Parliament (all party affiliations) and officials serving in senate departments. The group of stakeholders included union representatives, executives of organizations of employer representation, and pastors of Bremen's Catholic and Protestant parishes. Invitations were sent via personalized e-mail to the professional address, and reminders were sent if no response was received within two weeks. Excluding those where e-mails came back as undeliverable or if respondents reported their inability to participate due to language barriers (153), the Delphi sample achieved a response rate of 17.8 percent (n = 297).

Questionnaire design

The questionnaire involves scenarios in line with five basic themes at the intersection of AI and society: competition, wealth, communication, conflict, and assistance. These scenarios were delineated briefly in "How Will AI and Robotics Shape Society and Human Life in the Medium Run?" Each scenario refers to the reference year of 2030 and follows a clear structure: In an initial block, the scenario was deliberately pictured as a larger context and not as a narrowly defined situation. Participants first assessed the question "What do you expect: Will this scenario become a reality?" using an open response format and then reassessed *this pictured context* in the light of the frequency distribution of all assessments obtained to then in the Delphi sample. In a subsequent block, each respondent was asked to rate the dimensions involved in that context *also separately* – employing the standard response scale "not at all", "probably not", "possibly", "quite probable", and "quite certain" throughout most of the survey. In the following, Table 20.A1 reports on findings from the initial scenario blocks, and Table 20.A2 presents a small selection of ratings of single situational dimensions of one of the scenarios, in fact, the "communication scenario".

Findings from the Delphi survey

Table 20.A1 Will the scenario have become a reality in 2030, the reference year of each scenario?

	Quartiles			*Agreement*	*Rank correlation*			
	Q_1	Q_2	Q_3	κ	*Kendall's* τ_b			
Scenario					*Wealth*	*Comm.*	*Conflict*	*Assistance*
Competition	1.8	2.4	3.1	0.84	−0.02	0.14	0.15	0.01
Wealth	2.0	2.7	3.4	0.83		0.09	−0.06	0.01
Communication	2.1	2.9	3.8	0.81			0.08	0.15
Conflict	2.6	3.6	4.2	0.77				0.04
Assistance	2.9	3.6	4.1	0.75				

Entries in a row: first, second, third interpolated quartiles of first assessments, weighted kappa of first assessment and reassessment in the light of the frequency distribution of the former, and Kendall's tau rank correlations. Weighted κ is defined as the probability of observed matches minus the probability of matches expected by chance, divided by one minus the probability of expected matches. That way, κ expresses the excess of observed over expected agreement as share in the maximal possible excess. A weighted κ of 0.84, for instance, indicates that the observed agreement of assessment and reassessment exceeds the expected agreement by 84 percent of the maximum possible excess. R package used for computation: "psych".

Table 20.A2 Expectations concerning aspects of future human–robot communication

			Probably not = included, quite probable = excluded
1.7	2.3	3.1	Robots tend to replace humans situationally in interpersonal communication
1.7	2.3	3.2	Counseling – Specialized robots provide psychological advice
1.8	2.3	3.0	Humans trust AI more than the human himself
2.0	2.7	3.5	Guidance – Cognitive AI-assistance in rational choice
2.0	2.8	3.6	Consultation – seek a first doctor's advice from a robot in telemedicine
			Probably not = excluded, quite probable = excluded -> focused on "possibly"
2.1	2.8	3.5	Lifelogging is followed by communication of humans with personal avatars about their continuously recorded life data and behavioral data
2.1	2.9	3.5	Digital assistants have become personal avatars as steady advisory life companions at home and en route.
2.2	3.0	3.8	Robots keep lonely people of different age company at home
			Probably not = excluded, quite probable = included
2.7	3.4	4.0	Robots keep old people company at home
2.6	3.8	4.3	Bots communicate as perfectly as humans
3.1	3.8	4.3	AI and robots take on more and more assistant functions in the life of humans and contribute much to their quality of life

Population survey

Sample design and adjustment for unit nonresponse

Following a quasi-randomization approach (Elliott & Valliant, 2017), the overall sample consists of a combined probability and non-probability sample. A probability sample of residents aged 18+ is drawn from the population register of the municipality of Bremen and used as a reference sample for the estimation of inclusion probabilities for an analog volunteer sample. This probability sample achieved a response rate of 2.5 percent (N = 108).

Based on the available register information (age, gender, urban district) and the random response model (Bethlehem, 2009), inclusion probabilities were estimated and used to derive weights for an adjustment of the probability sample for possible unit-nonresponse bias. We normalized this weight variable to a mean value of one to preserve the initial sample size. Step 2 takes this weighted probability sample as a basis for the estimation of inclusion probabilities of the analog volunteer sample (also N = 108). This estimation, too, is based on age and gender and also involves an indicator of the readiness for participating in surveys, that is, the willingness to participate in a follow-up survey as declared by the respondents at the end of the two samples. Adopting the random response model again, these estimated inclusion probabilities were also used to derive normalized weights for a compensatory sample weighting. An overall weighting variable is then obtained by collecting the normalized weights for the probability sample (step 1, reference: population register) and the normalized weights for the volunteer sample (reference: probability sample) into one overall weight variable. In a final step, the remaining sample bias was removed by adjusting this overall weight by reference to corresponding sample-census distributions of official statistics for Bremen, using the freshest available figures, i.e., for 2018). That way, the remaining sample bias according to education (overrepresentation of higher education in the initial samples) and gender (despite the previous weighting, the remaining underrepresentation of women in the samples) was removed. Overall (unweighted and weighted) sample size is 216 people aged 18+.

Table 20.A3 Attitudes towards robots and AI, seeking of AI-driven advice, and self-image: CFA factor loadings and interpolated quartiles of indicator variables

	Q1	*Q2*	*Q3*	*Loadings*
Scale: 1 = not at all, 2 = probably not, 3 = possibly, 4 = quite probable, 5 = quite certain				
	AI IS GOOD FOR SOCIETY			
Robots/AI good for society	3.0	3.8	4.6	0.85
Robots/AI necessary	3.5	4.5	5.0	0.71
	AI IS SAFE FOR HUMANS			
Reliable (error-free) technology	1.5	2.5	3.6	0.71
Safe technologies for humans	2.1	3.0	3.8	0.94
Trustworthy technologies	2.3	3.0	3.5	0.84
	AI IS TRUSTFULLY DEPLOYED			
Job search: Automated preselection of candidates by intelligent software would. . .				
. . . be geared to qualification alone	1.5	2.6	3.6	0.72
. . . effectively guard against discrimination	1.6	2.4	3.5	0.89
. . . guard against discrimination better than human preselection	2.2	3.1	4.0	0.90
	WOULD SEEK AI DRIVEN ADVICE			
Respondent would use a smartphone app as a personal advisor in the case of decisions of everyday life	1.6	2.5	3.6	0.93
Respondent would use a smartphone app as a personal advisor in the case of decisions about important life situations	1.3	2.1	3.1	0.95
	SELF-IMAGE: OPEN-MINDED			
Respondent is open-minded toward technological innovations	3.5	4.3	4.9	0.62
Respondent likes to be counted among the first to try out technological innovations	1.7	2.3	3.5	0.81
Respondent keeps up with the times	3.0	3.7	4.3	0.71

N = 216. The CFA treats all scales as 5-point ordinal scales using probit regression. Survey weights are employed to handle unit nonresponse and multiple imputations to handle item nonresponse (five imputed datasets, including 176 complete cases). The CFA attains an acceptable goodness of fit: $\text{chi}^2 = 175$, df = 174, $p = 0.46$; CFI/TLI = 1.0, RMSEA = 0.01; SRMR = 0.071. The computation of interpolated quartiles is based on weighted frequency distributions. Because these distributions involve minor percentages of "don't know" responses (1.3% on average), these "don't know" responses were recoded to the mid category "possibly", acting on the auxiliary assumption that both categories equivalently express maximal uncertainty. R packages employed in this analysis: Lavaan, semTools, mice, survey.

Fieldwork

25 November to 15 December 2019. Survey invitation via personalized letter post, including a link to the web questionnaire (probability sample) and via an advertisement in the local newspapers and an announcement on the homepage of the University of Bremen website (volunteer sample). More details in Engel (2020).

Table 20.A4 Feelings towards robots and AI: CFA loadings of this factor and interpolated quartiles of indicator variables

	Q1	*Q2*	*Q3*	*Loadings*
RESPONDENT FEELS AT EASE WITH THE ANTICIPATED FICTITIOUS SITUATION				
A robot keeps you company at home	1.4	2.2	3.1	0.88
Medically skilled robot undertakes the first diagnosis/care in a tele-consultation	1.3	2.2	3.2	0.82
Smart Home: A robot recognizes you by your voice or look and turns to you individually	1.3	2.3	3.3	0.90
Be driven through the city by a self-driving car	1.5	2.7	3.8	0.67
You are in need of care: a robot takes part in your care	2.0	2.9	3.4	0.77
You must undergo a surgery in which a robot assists the physician	2.6	3.2	4.1	0.67
A robot supports you at the workplace	2.7	3.3	4.0	0.72
A drone delivers post home to you	2.7	3.6	4.3	0.72

Scale: 1 = would feel very unwell, 2 = quite unwell, 3 = part/part, 4 = quite well, 5 = very well

On average, 2.8% "don't know" answers were involved (recoded to mid category)

Findings from the population survey

More on https://github.com/viewsandinsights/AI.

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