Are Robots Becoming Unpopular?

Changes in Attitudes towards Autonomous Robotic Systems in Europe

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Research Highlights

- Attitudes towards robots became more negative between 2012 and 2017.
- Attitudes towards robots assisting at work showed the strongest negative trend.
- Women with lower education evaluated robots more negatively.
- Countries with a larger share of older citizens evaluated robots more favorably.

Abstract

Many societies are on the brink of a robotic era. In the near future, various autonomous computer systems are expected to be part of many people's daily lives. Because attitudes influence the adoption of new technologies, we studied the attitudes towards robots in the European Union between 2012 and 2017. Using representative samples from 27 countries (three waves, total $N = 80{,}396$), these analyses showed that, within five years, public opinions regarding robots exhibited a marked negative trend. Respondents became more cautious towards the use of robots. This tendency was particularly strong for robots at the workplace, which are, despite the drop, still more positively evaluated than robots performing surgeries or autonomous cars. Attitudes were more positive among men and people in white-collar jobs. Moreover, countries with a larger share of older citizens evaluated robotic assistance more favorably. In general, these results highlight increasing reservations towards autonomous robotic systems in Europe.

Keywords: robots, automated systems, attitudes, Europe, workplace, changes

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Changes in Attitudes towards Autonomous Robotic Systems in Europe

Robotic systems have intrigued authors of fiction, scientists, and the general public for decades. Some prophecies made in science fiction have not materialized yet (e.g., the original movie Blade Runner's world of humans and humanlike robotic replicants was set in the year 2019; Scott, 1982), but the momentum of robotic technologies is strong. The sale of industrial robots as well as of service robots is projected to grow with double-digit margins within the next years (International Federation of Robotics, 2017) and new robotic product categories will become available soon. *Waymo*, Alphabet's autonomous car division, has begun testing driverless cars without a safety driver in the fall of 2017 (Wakabayashi, 2017). Robots assist in surgeries including procedures that are impossible to conduct without robotic support (Whipple, 2017), and the development of robotic technologies for the assistance in nursing and elderly care has flourished (Kachouie, Sedighadeli, Khosla, & Chu, 2014). The first mass marketed sex robot was announced to be distributed in the first half of 2018 (Kleeman, 2017). Thus, many societies are currently on the verge of a robotic era that, in all likelihood, will result in robots soon becoming common in the lives of many people worldwide.

The consequences of these imminent technological changes are controversially debated. Proponents of an optimistic outlook argue that robotic systems will support individuals and contribute to economic growth. On the flipside, critics argue that up to one-fifth of the global work force could lose their jobs by 2030 due to robotic systems (Manyika et al., 2017). In addition to these economic challenges, the increasing use of robotic systems in fields that, until very recently, had been considered a realm of human-human interactions (such as elderly care and nursing, or sex), and the eeriness of human-like but not perfectly human machines (Mori, 1970; Wang, Lilienfeld & Rochat, 2015) could increase concerns regarding the widespread use of robotic systems in everyday life and foster negative attitudes towards robots.

In the last years people have become more and more acquainted with the idea that robots will be part of our everyday lives. On the one hand, this is due to the massive amount of news stories featuring robotic innovations, and, on the other hand, very basic toy robots and cleaning robots have become available to mass markets. Against this background, what are the consequences for the development of attitudes towards robots over time? Some have argued that with the proliferation of robots in our society, attitudes will become more positive, given that the fear of innovations on the verge of category boundaries will be reduced with personal experience and familiarity (e.g., Appel, Krause, Gleich, & Mara, 2016; Zlotowski et al., 2015). Yet, a technology that incorporates potential positive consequences (support and assistance) and potential negative consequences (job loss, existential questions) could elicit an approach-avoidance conflict (cf. Lewin, 1951). Following Miller's model (Miller, 1944; see also Boyd, Robinson, & Fetterman, 2011) approach tendencies should be relatively strong as long as the technology is part of a remote future. With increasing immediacy of the technology, negative aspects and avoidance become more and more dominant. Thus, negative attitudes will be more and more likely, with robots increasingly being part of people's daily lives. Indeed, a recent representative survey (Smith & Anderson, 2017) found that adults in the United States were about twice as likely to voice worries as compared to enthusiasm about robots in the workplace. Similarly, most Americans were rather reluctant to embrace autonomous systems such as driverless cars or robots as caregivers. Thus, current public opinions towards robots in the United States seem to be cautious at best.

The present study extends these results to the European continent and, more importantly, scrutinized how attitudes towards robots have changed over time. We examined responses from more than 80,000 citizens of the European Union who participated in the Eurobarometer surveys in the years 2012, 2014, and 2017. Whereas prior studies had already reported partial results for one of the waves (wave 2012: e.g., Loffredo & Tavakkoli, 2016; wave 2014: e.g., Hudson, Orbiska, & Hunady, 2017), a systematic statistical analysis of changes of attitudes over time is missing so far. In addition to the average rating of robots, we were also interested in individual and country differences, as well as differences depending on the robots' tasks. In particular, we expected respondents' economic conditions and age to influence the evaluation of robotic agents. First, we assumed that workers with blue-collar jobs that have the highest risk of being replaced by automated systems (Manyika et al., 2017) and those without a job would evaluate robots more negatively. In addition, we also evaluated respective context effects. Societies with a larger share of unemployed people are likely to endorse robots more hesitantly (particularly robots assisting at the workplace), because these might further reduce the scarce job opportunities. In contrast, economies with a large technology sector or economies spending more money on research and development might be less restive facing technological changes because these technologies are already an important source of revenue and job opportunities in the country. Second, aging societies or older respondents were expected to embrace robotic assistance more openly because many European countries are already having increasing difficulties in satisfying the demands for elderly care (Greve, 2017). Robots might alleviate some problems in health care and support for elder citizens by taking over routine tasks in this field. Finally, we also evaluated differences with respect to gender and educational attainment because previous studies (Broadbent, Stafford, & MacDonald, 2009) suggested that men and individuals with higher education might hold more positive attitudes toward robots. Extending prior analyses, we also took into account potential nonlinear associations between variables that might have been hidden due to previous statistical procedures, given that prior analyses of attitudes towards robots were based on assumptions of linearity.

Method

Participants

Citizens of the member states of the European Union participated in one of three waves of the Eurobarometer studies, either in March 2012, December 2014, or March 2017

(European Commission & European Parliament, 2014, 2015, 2017). The Eurobarometer consists of repeated cross-sectional and cross-national surveys monitoring the public opinion on current trends in Europe. At each wave, a representative sample of its citizens aged 15 years or older was drawn in each of the 27 countries[1] using a multi-stage, random sampling design. The sample sizes in each country varied between 500 (Cyprus) and 1,572 (Germany) resulting in a total sample of N = 80,396 respondents (55% women). Their age ranged from 15 to 99 years (M = 50.27, SD = 18.21). About 47% of the respondents were currently employed or self-employed, whereas the rest was either retired or otherwise non-employed (e.g., homemakers, students, unemployed). All interviews were administered face-to-face by professional survey institutes in the respective national language.

Instruments

Comparable questionnaires for each language were constructed by a back-translation procedure from the basic English version to control for semantic equivalence. At the beginning of the interview, all respondents were provided with a standardized description of a robot. In this introduction a robot was defined as "a machine which can assist humans in everyday tasks without constant guidance or instruction, e.g. as a kind of co-worker helping on the factory floor or as a robot cleaner, or in activities which may be dangerous for humans, like search and rescue in disasters" (European Commission & European Parliament, 2015, p. 4). Subsequently, they rated their attitudes towards robots. *General appraisals of robots* were measured by asking respondents to rate their general evaluation of robots ("Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots?") and indicating their agreement with the statements that (a) robots are a good thing for societies because they help people and (b) robots are necessary as they can do jobs that are

[1] Croatia was excluded from the present analyses because it was not a member of the European Union until 2013 and, thus, did not participate in the first wave.

too hard or too dangerous for people on four-point scales from “totally agree” (0) to “totally disagree” (3). The three items were reverse coded and summed up to create a composite score ranging from 0 to 9. These scores had categorical composite reliabilities (Green & Yang, 2009) of $\omega = .80$, .76, and .78 at the three waves. Moreover, our analyses show that the scale exhibited approximate measurement invariance across measurement waves and countries, which allowed for valid comparisons across groups (for details see the supplemental material).

Task-specific attitudes towards robots were measured with four items asking the respondents how they personally felt about four things that could be done by robots: (a) having a medical operation performed on you by a robot, (b) having a robot assist you at work, (c) having a robot to provide services and companionship to elderly and infirm people, and (d) traveling in a driverless car. Responses were indicated on 10-point scales from “totally uncomfortable” (0) to “totally comfortable” (9). The two latter items were only included in 2014 and 2017. The exact wording of these items is given in the supplemental material.

To study potential differences between countries, we acknowledged four *country-level indices* that we obtained from statistics provided in the World Bank (2017) database: (a) The share of older people in a country was indicated by the percentage of the population aged 65 or older, (b) the economic importance of the technology sector was reflected by the percentage of high-technology exports of all manufactured exports, (c) a country’s research investment was calculated by averaging two *z*-standardized indicators ($r = .90$, $p < .001$), that is, the number of persons in research and development (R&D) per million people and the percentage of R&D expenditure of the gross domestic product, and finally (d) the unemployment rate was given as the share of the labor force without work seeking employment. In addition, we used the geographical position of each country within Europe, as reflected by its latitude and longitude.[2]

Statistical Analyses

Given the large sample size, conventional inferential tests are less informative because even trivial effects become significant (cf. Kaplan, Chambers, & Glasgow, 2014; Secchi & Seri, 2017). Although we also report the results of appropriate statistical tests for all analyses ($\alpha = .005$; see Benjamin et al., 2018), our interpretations focus on relevant effect sizes. We considered standardized mean differences (d) of 0.20 and 0.30 and correlations (r) of .10 and .25 as small and moderate effects, respectively. These thresholds were based on a recent review summarizing the effects of field interventions on attitude change that identified average effect sizes around $d = 0.22$ in different domains that rarely exceeded $d = 0.33$ (cf. Albarracin & Shavitt, 2018). Because we implemented no explicit intervention but observed naturally occurring public opinions, we assumed that these values would represent the upper bound of effects to be expected in the present study. Because up to 13% of the respondents exhibited missing values on one or more variables (see Table 1), all analyses are based on multiple imputations where missing values were imputed 20 times using classification and regression trees (van Buuren, 2012). In all analyses, the data was weighted to derive parameter estimates that are representative for the European population. If not indicated otherwise, we used post-stratification weights that correct the sample composition (e.g., with regard to sex, age, and region) to match the corresponding population composition and population-size weights that correct the sample size for each country to correspond to its relative population size within the European Union (for more details see European Commission & European Parliament, 2017). All analyses were performed in *R* version 3.5.0

[2] Geographical information was retrieved from https://developers.google.com/public-data/docs/canonical/countries_csv.

(R Core Team, 2018). Multiple imputations were conducted with the *mice* package version 3.1.0 (van Buuren & Groothuis-Oudshoorn, 2011), whereas mixed effects regressions were estimates with *lme4* version 1.1-17 (Bates, Mächler, Bolker, & Walker, 2015).

Open Data and Open Material

Descriptive statistics for the focal variables are summarized in Table 1. Researchers accepting the legal restrictions can access the raw data used for the analyses (European Commission & European Parliament, 2014, 2015, 2017). Moreover, the analyses syntax used to reproduce the reported results is available within the *Open Science Framework* (Soderberg, 2018) at https://osf.io/w8phj.

Results

Current Attitudes towards Robots

When asked about attitudes towards autonomous robotic systems generally, those attitudes were quite positive. In 2017, the general appraisal of robots resulted in a mean rating of $M = 5.80$ ($SD = 1.96$) on a nine-point scale and, thus, indicated that on average Europeans held more positive rather than negative views of robots. However, there was some variability between the 27 member states of the European Union: the mean attitude scores for each country had a standard deviation of 0.43. The descriptive information in Figure 1 (left panel) illustrates these cross-country differences. For example, as compared to the average ratings in Europe, Danes ($M = 6.80$, $SD = 1.57$) and Swedes ($M = 6.63$, $SD = 1.66$) rated robots more positively, $d = 0.57$ ($t = 10.93$, $df = 14480$, $p < .001$) and $d = 0.47$ ($t = 10.62$, $df = 1632$, $p < .001$), whereas Greeks ($M = 4.95$, $SD = 2.16$) and French ($M = 5.40$, $SD = 2.07$) had more negative attitudes, $d = -0.42$ ($t = -9.80$, $df = 15569$, $p < .001$) and $d = -0.23$ ($t = -10.42$, $df = 286$, $p < .001$). In general, however, differences between countries accounted for rather little variance in attitude ratings (intraclass correlation ICC = .05); rather, most of the variance was attributed to differences between respondents (see more below).

Task-specific attitudes for robots performing various functions in the society exhibited some variability. Respondents were significantly more comfortable with robots assisting them at work (M = 4.18, SD = 3.02) as compared to robots performing medical operations (M = 3.19 SD = 3.04) or helping the elderly or infirm (M = 3.34, SD = 3.01): d = 0.33 (t = 36.26, df = 2799, p < .001) and d = 0.28 (t = 31.18, df = 4661, p < .001), respectively. Similar, they were less willing to travel in driverless, autonomous cars (M = 2.87, SD = 2.97), d = 0.44 (t = 49.48, df = 12150, p < .001). Again, differences in task-specific attitudes were primarily a result of differences between respondents and to a lesser degree a consequence of cross-country differences (ICCs = .03 to .06).

Changes in Attitudes towards Robots

Five-year changes in attitudes were examined by comparing the average attitude ratings between the three waves (see Figure 2). These analyses showed that Europeans became more skeptical towards autonomous robotic agents. The means of the general appraisal of robots were lower in 2017 than they were in 2014, d = -0.10 (t = -10.31, df = 551, p < .001) or in 2012, d = -0.21 (t = -22.53, df = 1380, p < .001). In particular, the attitude scores regarding robots assisting at work exhibited a marked decline across the five-years span, d = -0.30 (t = -32.89, df = 1218, p < .001). Other task-specific attitudes such as the attitudes towards using robots for medical operations showed less variation, d = 0.09 (t = 10.39, df = 2815, p < .001). Again, we observed some differences between European countries. The descriptive information in Figure 1 (right panel) indicated that changes in general attitudes towards robots seemed to be slightly stronger in northern countries as compared to western regions. For example, in Denmark and Sweden mean attitude ratings were more negative in 2017 as compared to 2012, d = -0.28 (t = -3.39, df = 52484, p = .001) and d = -0.41 (t = -6.45, df = 11372, p < .001), respectively. In contrast, they hardly changed in Italy (d = -0.07, t = -1.28, df = 95378, p = .202) or in Portugal, d = 0.02 (t = 0.59, df = 300, p = .553).

Predictors of Attitudes Towards Robots

To identify the most important variables predicting attitudes towards robots, the general appraisal ratings were regressed on two dummy coded indicators representing the measurement wave (using the first wave as reference category) and the respondent characteristics of gender (coded 0 for men and 1 for women), age (in decades), years in education, and employment status (dummy coded using white-collar workers as reference). These analyses included respective random effects to account for the nesting of respondents within countries (Bates et al., 2015). As summarized in Table 2 (Model 1), on average, men held significantly ($p < .001$) more favorable attitudes towards robots than women ($d = 0.21$). Similarly, an increase of three years in education (i.e., about 1 *SD*) resulted in a shift of attitude ratings of about $d = 0.19$ ($p < .001$) reflecting a positive link between education and attitudes towards robots. Moreover, working in a white-collar profession as compared to a blue-collar profession or non-employment was associated with slightly more positive attitudes, $d = 0.08$ ($p < .001$) and $d = 0.07$ ($p < .001$). In contrast, an individual's age had a negligible influence on attitudes towards robots: an age difference of 10 years changed respective ratings by less than one percent. Highly similar results were observed for the four task-specific attitudes (Table 3). Holding more favorable views on robots performing medical operations, assisting at work, helping the elderly, or driving cars was more likely for men, individuals with longer education, and those in white-collar professions.

Potential differences between European countries were studied by extending the previous regression model and including six country-level characteristics, that is, the percentage of older citizens, percentage of technological exports, research investments, unemployment rates, and the geographical latitude and longitude (see Model 2 in Table 2). Countries with a larger share of older citizens exhibited somewhat more positive attitudes ($p = .001$). However, the respective effect was rather small: a difference of about 2.5 points (i.e., about 1 *SD*) in the proportion of inhabitants older than 65 years corresponded to a shift in general appraisals of robots by about $d = 0.22$. Thus, older societies were more inclined to endorse robotic assistance than younger ones. Moreover, an increase in unemployment rates of about 5 points (i.e., about 1 *SD*) corresponded to a change in attitudes of about $d = 0.11$ ($p = .003$) indicating a very small positive relationship between unemployment and attitudes towards robots. In contrast, other macro-economic variables such as differences in research investments or the percentage of technological exports did not explain attitude variations across Europe (i.e., R^2 less than 1 percent). Regarding the geographical position within Europe, Northern countries showed significantly ($p = .0046$) more positive attitudes towards robots than countries located in the south.

Finally, we focused on potential nonlinear relationships and examined whether the identified subgroup differences were more pronounced for respondents with either more negative or more positive views of robots. To this end, quantile regression analyses (Koenker, 2005) explored the effects of individual differences on the general appraisal of robots at the bottom quantile (.25), the median quantile (.50), and the upper quantile (.75). The standardized regression coefficients at these quantiles are summarized in Figure 3. These analyses showed that the identified gender effect was rather robust across different attitudinal levels: Gender differences were $d = 0.25$ ($p < .001$), $d = 0.21$ ($p < .001$), and $d = 0.24$ ($p < .001$) at the bottom, median, and upper quantile. Similarly, age and educational effects were consistent across different quantiles. However, differences between respondents with and without a job were more pronounced at the bottom quantile. Having a white-collar as compared to no employment increased the bottom quantile by about $d = 0.18$ ($p < .001$), whereas no difference was observed at the upper quantile, $d = 0.00$ ($p = 1.000$). Thus, among respondents with a negative view of robots, those employed in white collar jobs were underrepresented; in contrast, among those with favorable attitudes towards robots job status was of limited relevance.

Discussion

Modern societies are becoming increasingly dependent on automated technologies. The continuous flow of city traffic, for example, would not be possible without automated computer controls governing the signaling systems throughout the road networks. Autonomous robotic systems are an imminent continuation of this development. Robotic systems promise to take over everyday chores in, for example, transportation (Wakabayashi, 2017), education (Salvini, Korsah, & Nourbakhsh, 2016), and health care (Kachouie et al., 2014). Robots are expected to profoundly change how people work, travel, and organize their private lives. However, the successful diffusion of a new technology requires general acceptance in a society (Batinic, Appel, & Gnambs, 2016; Broadbent et al., 2009); otherwise the adoption of new innovations is destined to fail. Thus, policy makers and stakeholders in the technology sector need to know how customers and the general public feel about robotic agents to plan and implement appropriate interventions such as legislative measures (e.g., the liability in case of accidents with driverless cars) or information campaigns (e.g., the benefits of robotic assistance in elderly care). Therefore, it is important to continually monitor attitudes towards robots and study how these attitudes evolve over time.

Key Findings on Attitudes Towards Robots in Europe

The present study relied on a unique large-scale dataset examining the attitudes towards robots in the European Union over five years. These analyses showed that Europeans' attitudes towards robots were rather complex. When asked about robots in a general, rather abstract way, they were rated quite favorably; thus, robots were perceived as a potentially useful technology enriching people's lives. However, as soon as respondents considered concrete applications of robotic services that might soon become reality, they were more cautious. Currently, many people seem to have profound concerns in accepting robotic assistance for medical operations, in elderly care, or in the form of driverless cars. Importantly, within the five years between 2012 and 2017 Europeans have become more and more wary towards robots. Remarkably, the size of the respective effect (up to d = -0.21 to -0.30) was quite similar to many intervention studies that were explicitly designed to elicit an attitude change (see Albarracin & Shavitt, 2018), despite the fact that the current study observed naturally occurring change trajectories in the public opinion towards robots without the implementation of any intentional manipulation. More specifically, attitudes towards robots in the workplace are still more positive than attitudes towards robots in other applied fields, but they have also shown the most remarkable change. These increasing worries are not without cause; by 2030 about a fifth of all jobs is projected to be replaced by robots (Manyika et al., 2017). Thus, the increased media attention and public discussion of robots in recent years might have shifted public opinions in a more critical direction.

We observed notable differences in attitudes between European countries. Citizens of northern countries reported, on average, more positive views of robots. Whereas macroeconomic indicators were unable to explain these differences, the age distribution within a country was identified as a relevant factor. Societies with a larger share of older inhabitants expressed more positive views towards robots. This is not unexpected because in ageing societies robots might compensate for shortages in elderly and outpatient care. Even today, respective demands are insufficiently met in many regions because qualified personnel are difficult to find (e.g., Hodgkin, Warburton, Savy, & Moore, 2017). Automated systems could alleviate these problems by taking over routine tasks and, for example, deliver meals or medications in hospitals, aid in rehabilitation therapy or personal hygiene, or assist in shopping for everyday commodities (Broadbent et al., 2009). Robotic companions such as *Paro* or *Aibo*, a robot seal and a robot dog, might even have positive psychosocial effects and, for example, reduce loneliness in old age (Robinson, MacDonald, Kerse, & Broadbent, 2013).

Respondent characteristics were particularly important in explaining differences in attitude ratings. Similar to survey data from the United States (Smith & Anderson, 2017) attitudes towards robots among European citizens were more negative among women as compared to men. This has previously been attributed to gender differences in technology-related anxieties because men associate more positive emotions towards automated systems, whereas women express more negative emotions (e.g., Hohenberger, Spörrle, & Welpe, 2016). However, the most skeptical views were held by respondents with lower education in blue-collar professions or out of the labor force who are likely to be the most affected by the introduction of robots in the workplace. Manual jobs with routine tasks have the highest danger of being replaced by automation (Manyika et al., 2017). In contrast to other studies (e.g., Hudson et al., 2017) we found no pronounced age differences in the evaluation of robots. Although older respondents exhibited slightly more negative attitudes, these effects were small as compared to other sociodemographic characteristics (e.g., gender, education). Remarkably, the lack of a substantial age effect on the individual level is in sharp contrast to the previously identified context effect of a country's age distribution. These results imply that the context of an aging society is more relevant for the development of positive attitudes towards robots than the individual age of the respondent. Societies that are older on average seem to embrace robotic assistance more readily because of a shortage of young people available to do the necessary chores in the society (e.g., in elderly care). In contrast, the individual age seems to have little influence on attitudes towards robots.

Study Limitations

Some weaknesses might limit the generalizability of the present findings. First, the results pertain to a large-scale observational study documenting the current attitudes and the respective changes within the last five years. The study was unable to shed light on causal processes explaining differences in attitudes towards robotic systems beyond mere socio-demographic effects. For this purpose, quantitative lab studies are needed that can also pursue more fine-grained and causal questions. Second, economic constraints associated with large-scale social surveys only allowed for the administration of rather short measurement instruments. Because short-scales sometimes have a poor power to identify individual-differences in change (Gnambs & Buntins, 2017), the reported moderating effects on attitude change might represent a lower bound of the true effect. It would be informative to replicate the findings with more elaborate measuring scales (cf. Nomura, Kanda, & Suzuki, 2006). On a related note, large-scale social surveys cannot replace smaller surveys that may be limited in their own ways (e.g., non-representative, limited to one specific sub-population such as undergraduates, lack of societal context), but that allow examining a broader set of individual difference measures (e.g., Lischetzke, Izydorczyk, Hüller, & Appel, 2017; MacDorman & Entezari, 2015). Finally, the identified changes in attitudes toward robots pertain to population changes (i.e., aggregated change over time). Because different participants were sampled at each measurement occasion, within-individual changes could not be examined. More precise estimates of change processes would be available in true longitudinal designs that survey the same respondents repeatedly over time.

Outlook on Future Studies

The findings in this study presented a snapshot of current attitudes towards robots and their changes within the last five years. Future research is needed to extend these results in several ways. For one, our study did not scrutinize the specific mental model that respondents held of robots. Rather, we examined the evaluation of a generic robot without explicating a specific robotic system. However, robots come in many forms and sizes. Some resemble humans (e.g., *Sophia*; cf. Greshko, 2018) or animals (e.g., the robot seal *Paro*), whereas the shape of others are more strongly determined by their functionality (e.g., automatic dust cleaners). When discussing robots and their impact on our society, most people tend to have a default conceptualization of a robot with strong anthropomorphic features (Phillips, Ullman, de Graaf, & Malle, 2017). Thus, the typical mental model of a robot shares many human-like qualities. At present, a widespread proliferation of humanoid robots in our everyday lives is still theory (or fiction). As of yet, most people have no personal experience with human-like robots. Because lack of familiarity can contribute to uncertainty and negative feelings

(Buchner, Wurhofer, Weiss, & Tscheligi, 2013; Koay et al., 2007), this might explain the overall negative trend in general attitudes towards robots currently prevalent in Europe. However, nowadays different kinds of non-humanoid robots are already in widespread use. For example, many people use virtual automated assistants such as *Alexa* or *Google Home* in their homes (Këpuiska & Bohouta, 2018) or implicitly interact with warehouse robots when ordering products online (Bogue, 2016) without even realizing it. These robots are quite different from the classic anthropomorphic or zoomorphic mental model that is implicitly shared by many people. Therefore, future studies need to monitor more fine-grained attitudes towards different types of robotic systems.

More research is also needed to uncover processes shaping the observed attitude changes. For example, we observed notably stronger changes in attitudes towards robots assisting at work between 2014 and 2017 as compared to the first two measurement waves (2012 vs 2014). It could be that the stronger negative trend is a reflection of an increased media attention on how automatic systems are going to change our lives. News features and television documentaries regularly emphasize that robots are on the verge of replacing many jobs so far reserved for humans and are also responsible for decreasing wages in various professions. It is conceivable that these ongoing warnings contribute to the negative perception of robotic assistants at work. Future studies should evaluate to what degree controversial media debates shape negative attitudes towards robots by disproportionally highlighting potential disadvantages of robots while downplaying their benefits. Potentially changing attitudes should also be evaluated when more and more diverse autonomous robotic systems (e.g., driverless cars) start to be mass marketed. It is likely that robotic systems will be more readily accepted with increasing familiarity. When people gain hands-on experience with their usefulness, their evaluation of robots is expected to rise (Savela, Turja, & Oksanen, 2017; see also Appel et al., 2016). In this vein, it could also be informative to examine various personality characteristics that have been associated with the diffusion of innovations (e.g., opinion leadership) to predict attitude change and the adoption of new robotic services within social groups (e.g., Gnambs & Batinic, 2012; Jansson, Nordlund, & Westin, 2017).

Finally, little is known regarding systematic cross-cultural differences in the evaluation of robots. Is the observed negative attitude towards robots a universal trend around the world? We compared 27 countries and found only few systematic differences within Europe. Similar negative perceptions of robots were also observed in a recent representative survey in the United States (Smith & Anderson, 2017). At least in Europe and North America, a negative trend in attitudes seems to be prevalent. Although popular belief suggests that Japanese (and many other Asian societies) love robots, so far no conclusive support was found for this conjecture. Rather, apart from direct experience with robots, different cultures exhibit more similarities than differences in attitudes towards robots (Haring, Mougenot, Ono, & Watanabe, 2014; MacDorman, Vasudevan, & Ho, 2009); others even found more positive perceptions among, for example, Australian as compared to Japanese participants (Haring, Silvera-Tawil, Matsumoto, & Watanabe, 2014). Overall, there is a dearth of systematic cross-cultural comparisons on attitudes towards robots that allow generalizable conclusions. More research is needed to uncover cultural differences such as variations in generalized trust in automation or openness that might influence the willingness to adopt robots (e.g., Bartneck, Suzuki, Kanda, & Nomura, 2007; Chien, Sycara, Liu, & Kumru, 2016).

Conclusion

Prevalent theories in social psychology such as the theory of planned behavior (Ajzen, 1991) or the technology acceptance model (Venkatesh, Morris, Davis, & Davis, 2003) emphasize the importance of attitudes as precursors of technology acceptance and usage. This study summarized the public attitudes towards robots in the European Union, the second largest economy in the world, and respective changes across time, examining potential predictors of attitudes towards robots on the country level, as well as on the individual level. A multi-level approach to monitoring how the general public feels about robotic agents informs theory and research and is particularly important for policy makers and stakeholders in the technology sector. After all, robotic systems are expected to soon become an indispensable factor in many societies.

On average, attitudes towards robots in Europe have become more negative between 2012 and 2017. This was in part due to the fact that the attitudes in once robot-optimistic countries got less optimistic. Moreover, attitudes towards robots at the workplace, once particularly positive, have become less positive. Being male, highly educated, and living in a country with a larger percentage of older citizens predicted more positive attitudes. It appears that particularly individuals who have less to gain and more to lose see robots critically. The negative trend in robot attitudes should alert stakeholders in politics and the industry to take reservations regarding the proliferation of autonomous robotic systems seriously.

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Table 1.

Descriptive Statistics and Correlations between Study Variables

						Correlations												
			M	*SD*	FMI	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	*M*	*SD*	FMI
Wave 1: March 2012	1.	General appraisal of robots	6.20	1.89	0.09		.35	.52	.36	.32	-.12	-.07	.20	-.04	-.04	6.01	1.96	0.11
	2.	Medical operation by robot	2.90	2.98	0.02	.30		.42	.38	.45	-.15	-.04	.20	-.04	-.08	2.99	3.12	0.06
	3.	Assisting at work by robot	5.09	3.00	0.04	.48	.34		.40	.38	-.13	-.13	.24	-.05	-.05	5.00	3.09	0.06
	4.	Help for elderly/infirm by robots								.39	-.12	-.13	.14	-.01	-.04	3.44	3.17	0.05
	5.	Travel in autonomous cars									-.16	-.17	-.22	-.01	-.10	2.71	3.08	0.05
	6.	Sex	0.52	0.50	0.00	-.12	-.13	-.12				.06	-.06	-.10	.13	0.52	0.50	0.00
	7.	Age	46.82	18.50	0.00	-.10	.00	-.11			.06		-.43	-.18	.29	47.40	18.41	0.00
	8.	Years in education	5.36	2.87	0.01	.23	.16	.23			-.03	-.44		-.09	-.16	5.54	2.84	0.02
	9.	Blue-collar workers [a]	0.24	0.43	0.00	-.02	.01	-.02			-.11	-.19	-.10		-.58	0.24	0.43	0.00
	10.	Non-employed [a]	0.51	0.50	0.00	-.06	.06	-.07			.12	.28	-.14	-.56		0.51	0.50	0.00
Wave 3: March 2017	1.	General appraisal of robots	5.79	1.96	0.13													
	2.	Medical operation by robot	3.19	3.04	0.05	.36												
	3.	Assisting at work by robot	4.17	3.02	0.06	.51	.49											
	4.	Help for elderly/infirm by robots	3.34	3.01	0.04	.38	.47	.52										
	5.	Travel in autonomous cars	2.87	2.97	0.03	.37	.53	.52	.49									
	6.	Sex	0.52	0.50	0.00	-.12	-.15	-.14	-.12	-.16								
	7.	Age	48.28	18.78	0.00	-.13	-.08	-.15	-.18	-.20	.06							
	8.	Years in education	5.67	2.85	0.02	.23	.22	.24	.21	.23	-.04	-.43						
	9.	Blue-collar workers [a]	0.23	0.42	0.00	-.01	.00	-.03	-.01	.00	-.18	-.10	-.09					
	10.	Non-employed [a]	0.51	0.50	0.00	-.10	-.10	-.04	-.07	-.12	.31	.12	-.18	-.56				

Wave 2: December 2014

Note. The *N*s are 26,751, 26,792, and 26,853 in 27 countries for the three waves. FMI = Fraction of missing information. Based on 20 imputed samples. [a] Dummy-coded with white-collar workers as reference category. All correlations greater than $|r| \geq .02$ are significant at $p < .005$.

Table 2.

Mixed-Effects Regression Analyses Predicting General Appraisals of Robots

		Model 1			Model 2		
	Predictors	*B*	(*SE*)	β_y	*B*	(*SE*)	β_y
	Intercept	6.64	(0.08)		2.70	(0.84)	
	Respondent characteristics						
1.	Measurement occasion: [a]						
	- 2014	-0.21*	(0.02)	-0.11	-0.27*	(0.03)	-0.14
	- 2017	-0.44*	(0.02)	-0.22	-0.53*	(0.04)	-0.27
2.	Gender (0 = men, 1 = women)	-0.42*	(0.02)	-0.21	-0.42*	(0.02)	-0.21
3.	Age (in decades) [b]	-0.01	(0.01)	-0.00	-0.01	(0.01)	-0.00
4.	Years in education [b]	0.13*	(0.00)	0.06	0.13*	(0.00)	0.06
5.	Employment status: [c]						
	- blue-collar workers	-0.16*	(0.02)	-0.08	-0.16*	(0.02)	-0.08
	- non-employed	-0.13*	(0.02)	-0.07	-0.13*	(0.02)	-0.07
	Country characteristics						
6.	Percentage of older citizens				0.09*	(0.03)	0.05
7.	Unemployment rate				0.02*	(0.01)	0.01
8.	Percentage of technological exports				0.01	(0.01)	0.00
9.	Research investments				-0.00	(0.08)	-0.00
10.	Geographical latitude				0.04*	(0.01)	0.02
11.	Geographical longitude				0.01	(0.01)	0.00
	Random variance	0.16			0.19		
	Residual variance	3.42			3.42		

Note. N = 80,396. Mixed effects regression analyses on 20 imputed datasets. B = Unstandardized regression weight, SE = Standard error of B, β_y = Regression weight standardized with respect to the dependent variable (equal to Cohen's d for dichotomous variables). [a] Dummy-coded with 2012 as reference category, [b] Grand-mean centered [c] Dummy-coded with white-collar workers as reference category.

* $p < .005$

Table 3.

Mixed-Effects Regression Analyses Predicting Task-Specific Attitudes towards Robots

		Medical operations			Assisting at work			Help elderly and infirm			Travel in driverless car		
		B	(*SE*)	β_Y	*B*	(*SE*)	β_Y	*B*	(*SE*)	β_Y	*B*	(*SE*)	β_Y
	Intercept	3.55	(0.14)		5.66	(0.15)		3.79	(0.15)		3.45	(0.10)	
1.	Measurement occasion: [a]												
	- 2014	0.06	(0.03)	.02	-0.13*	(0.03)	-.04						
	- 2017	0.22*	(0.03)	.07	-0.97*	(0.03)	-.31	-0.10*	(0.03)	-.03	0.15*	(0.03)	.05
2.	Gender (0 = men, 1 = women)	-0.80*	(0.02)	-.26	-0.73*	(0.02)	-.23	-0.69*	(0.03)	-.22	-0.87*	(0.03)	-.28
3.	Age (in decades) [b]	0.08*	(0.01)	.03	-0.09*	(0.01)	-.03	-0.18*	(0.01)	-.06	-0.17*	(0.01)	-.05
4.	Years in education [b]	0.17*	(0.01)	.06	0.18*	(0.01)	.06	0.09*	(0.01)	.03	0.14*	(0.01)	.05
5.	Employment status: [c]												
	- blue-collar workers	-0.34*	(0.03)	-.11	-0.26*	(0.03)	-.08	-0.27*	(0.04)	-.09	-0.49*	(0.04)	-.16
	- non-employed	-0.47*	(0.03)	-.15	-0.03	(0.03)	-.01	-0.05	(0.03)	-.02	-0.46*	(0.03)	-.15
	Random variance	0.45			0.60			0.56			0.22		
	Residual variance	8.42			8.17			8.59			8.09		

Note. N = 80,396. Mixed effects regression analyses on 20 imputed datasets. *B* = Unstandardized regression weight, *SE* = Standard error of *B*, β_Y = Regression weight standardized with respect to the dependent variable (equal to Cohen's *d* for dichotomous variables), [a] Dummy-coded with 2012 as reference category, [b] Grand-mean centered [c] Dummy-coded with white-collar workers as reference category.

* $p < .005$

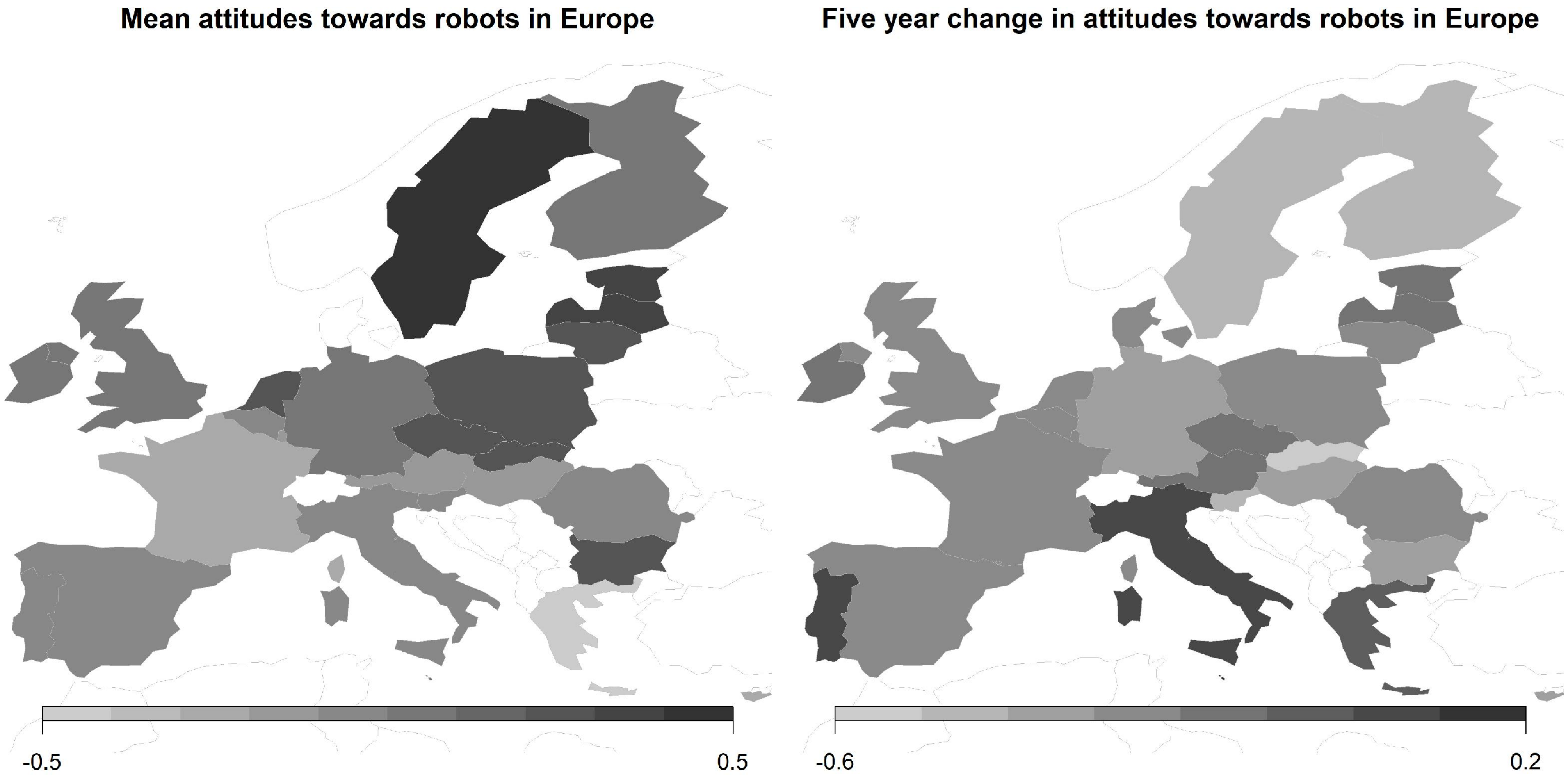

Figure 1. Attitudes towards robots in Europe (*z*-standardized). Left: Mean attitudes in 2017; light gray indicates more negative attitudes, whereas dark gray reflects more positive attitudes. Right: Changes in mean attitudes between 2012 and 2017; light gray indicates more negative attitudes in 2017 as compared to 2012, whereas dark gray reflects more positive attitudes in 2017.

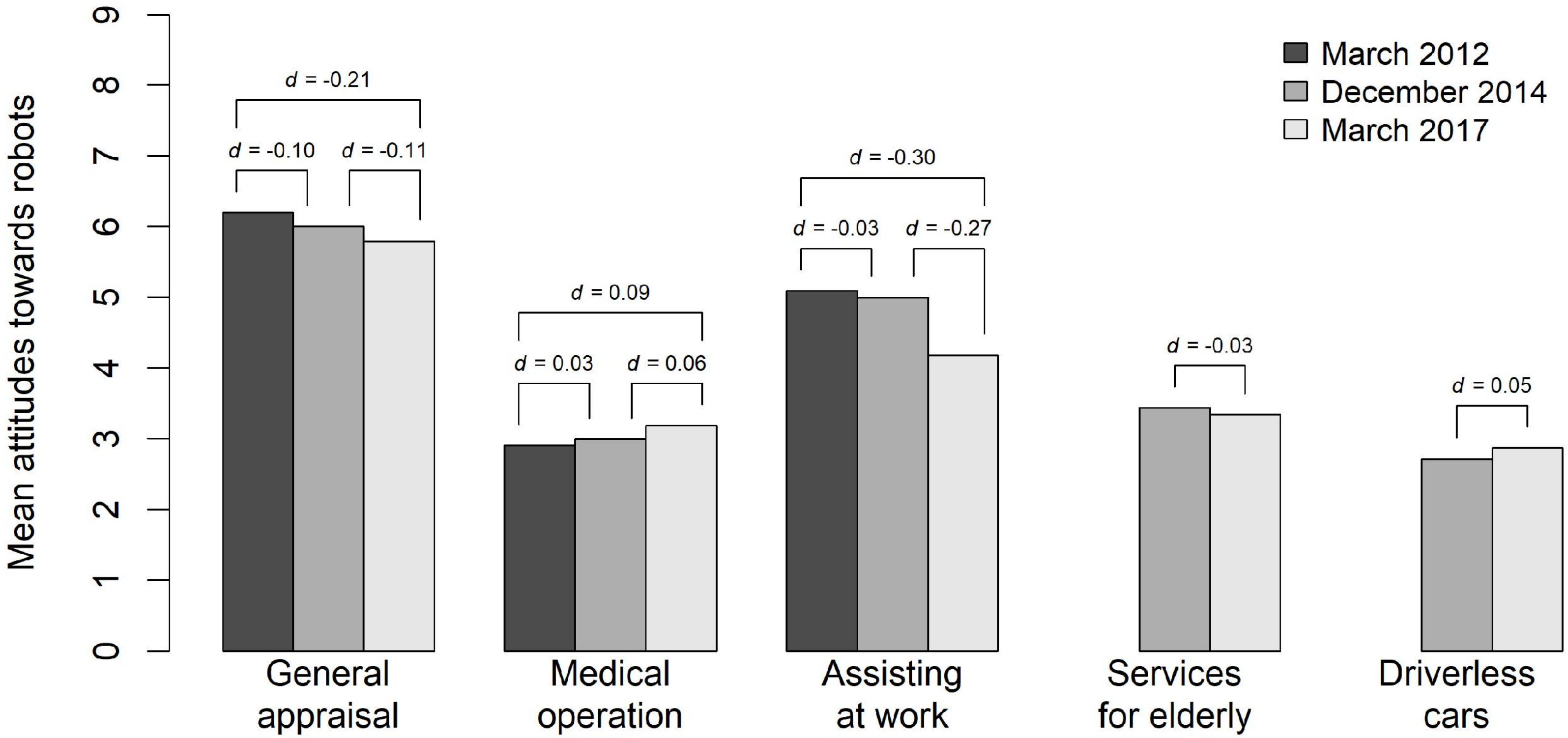

Figure 2. Change in mean attitudes towards robots within five years.

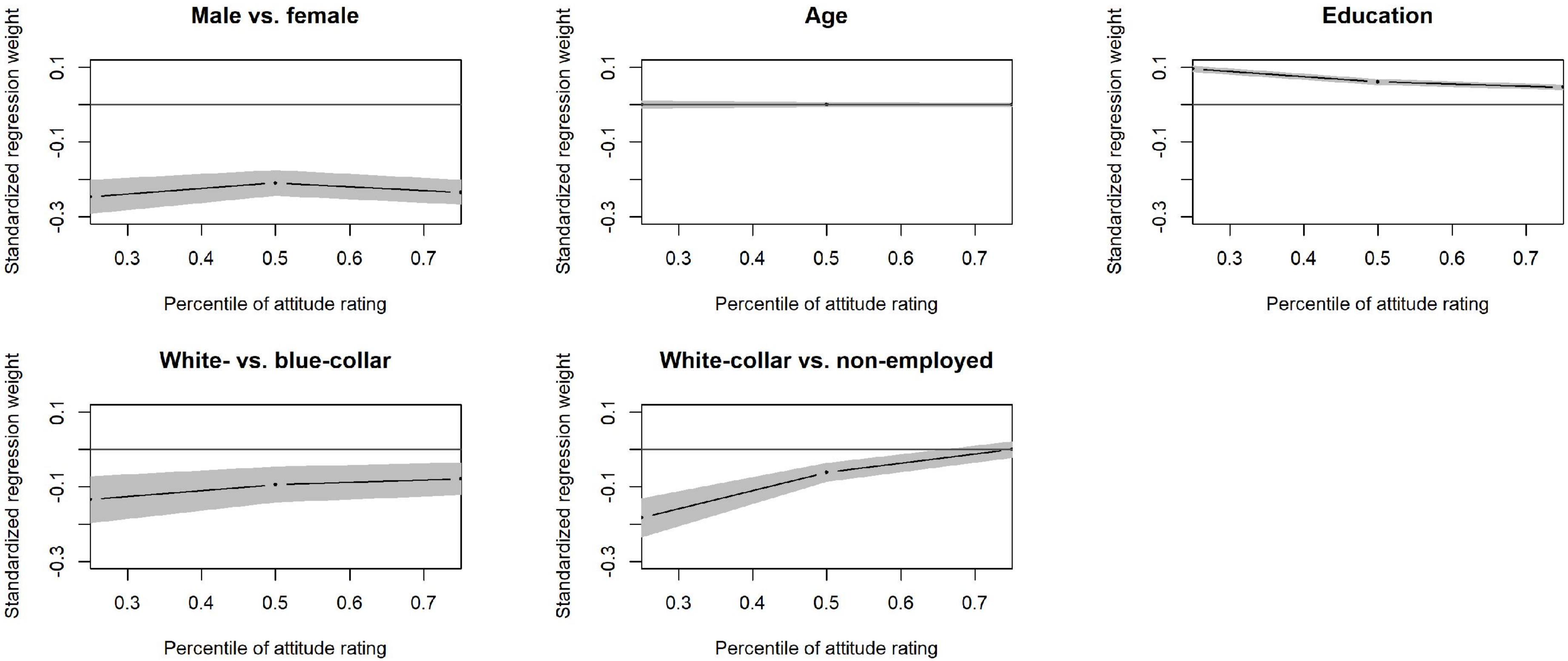

Figure 3. Standardized coefficients from quantile regressions at 25%, 50%, and 75% percentiles (black dots) with 95% confidence intervals (gray region)

Supplemental Material for

"Are Robots Becoming Unpopular? Changes in Attitudes towards Autonomous Robotic Systems in Europe"

Survey Instrument

Standardized description of a robot

"A robot is defined as a machine which can assist humans in everyday tasks without constant guidance or instruction, e.g. as a kind of co-worker helping on the factory floor or as a robot cleaner, or in activities which may be dangerous for humans, like search and rescue in disasters. Robots can come in many shapes or sizes and some may be of human appearance. Traditional kitchen appliances, such as a blender or a coffee maker, are not considered as robots." (European Commission & European Parliament, 2015, p. 4)

Attitudinal items (European Commission & European Parliament, 2014, 2015, 2017)

	March 2012	December 2015	March 2017
1.	Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots?	Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots?	Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots **and artificial intelligence**?
2.	Robots are a good thing for society, because they help people.	Robots are a good thing for society, because they help people.	Robots **and artificial intelligence** are a good thing for society, because they help people **do their jobs or carry out daily tasks at home**.
3.	Robots are necessary as they can do jobs that are too hard or too dangerous for people.	Robots are necessary as they can do jobs that are too hard or too dangerous for people.	Robots are necessary as they can do jobs that are too hard or too dangerous for people.
	Here is a list of things that could be done by or with robots. For each of them, please tell me, using a scale from 1 to 10, how you would personally feel about it. On this scale, '1' means that you would feel "totally uncomfortable" and '10' means that you would feel "totally comfortable" with this situation		
4.	Having a medical operation performed on you by a robot.	Having a medical operation performed on you by a robot.	Having a medical operation performed on you by a robot.
5.	Having a robot assist you at work **(e.g. in manufacturing)**.	Having a robot assist you at work **(e.g. in manufacturing)**.	Having a robot assist you at work.
6.		Having a robot to provide services and companionship to elderly or infirm **people**.	Having a robot to provide **you** services and companionship **when** infirm or elderly.
7.		**Travel yourself in an autonomous or** driverless car.	**Being driven in a** driverless car **in traffic**.

Note. Changes in item wording are in bold.

Measurement Invariance of the General Appraisal of Robot Scale

Valid comparisons across different measurement occasions and countries requires that the administered instruments function comparably and capture identical constructs in similar ways. Therefore, measurement invariance was examined across the three measurements waves in 2012, 2014, and 2017 using a multi-group confirmatory factor analysis for ordered-categorical data with a mean and variance adjusted diagonally weighted least square estimator (Liu, Millsap, West, Tein, Tanaka, & Grimm, 2017). For each wave, an independent group was specified that modeled a single latent factor with three items. The latent factors were identified by constraining the loading of the second item to 1. To account for the clustering of respondents within different countries cluster-robust standard errors were estimated (Cameron & Miller, 2015). Measurement invariance was investigated by comparing three models with increasingly restrictive constraints. The configural invariance model placed no constraints across the three groups and estimated independent factor models for each wave. Because latent factors with three indicators are just-identified, no goodness-of-fit indices are available for this model. The metric invariance model constrained the factor loadings across groups and tested if the latent factors were measured comparably. Metric invariance is a prerequisite to compare latent variances and covariances. Finally, scalar invariance was tested by additionally constraining the item thresholds across groups. Scalar measurement invariance allows latent mean-level comparisons between groups. Model fit was evaluated in line with conventional standards (Schermelleh-Engel, Moosbrugger, & Müller, 2003) with a *Comparative Fit Index* (CFI) $\geq .95$ and a *Root Mean Square Error of Approximation* (RMSEA) $\leq .08$ indicating an "acceptable" model and a CFI $\geq .97$ and a RMSEA $\leq .05$ reflecting a "good" fitting model. Because changes in practical fit indices such as the CFI perform rather poorly for ordered-categorical data (Sass, Schmitt, & Marsh, 2014), model comparisons were made using the scaled difference chi-square test (Satorra & Bentler, 2010). Following Liu and colleagues (2017), the practical significance of differences in measurement parameters across the three measurement waves were evaluated using sensitivity analyses that compared the model-predicted probabilities of choosing specific response categories. These probabilities were calculated based on measurement models with different levels of invariance constraints. We used differences in the model-predicted probabilities from two invariance models as an effect size of the violation of measurement invariance.

Table S1.

Model Fit for Test of Measurement Invariance across Waves

Model	χ^2	*df*	CFI	RMSEA	Comp.	$\Delta\chi^2$	Δdf
1. Configural invariance	0.00	0	1.000	0.000			
2. Metric invariance	14.22	4	0.999	0.010	Model 1	7.47	4
3. Scalar invariance	45.80^*	20	0.997	0.007	Model 2	35.17^*	16

Note. χ^2 = Chi-squared model discrepancy, *df* = Degrees of freedom, CFI = Comparative fit index, RMSEA = Root mean squared error of approximation, Comp. = Comparison model, $\Delta\chi^2$ = Scaled differences chi-squared, Δdf = Difference in degrees of freedom, *p* = *p*-value for difference test.
* $p < .005$

The results for the three invariance models and the respective model comparisons in Table S1 show that metric invariance across the three measurement waves was supported ($p = .113$), whereas the difference test for scalar invariance was significant ($p = .004$). However, the practical fit indices did not indicate a pronounced misfit of the scalar invariance model with a CFI of .997 and a RMSEA of .007. Moreover, the differences in the model-predicted response probabilities (see Table S2) showed only marginal differences between the metric invariance model (with constraints on the factor loadings) and the scalar invariance model (with constraints on the factor loadings and thresholds). All discrepancies were small (i.e., < .05; cf. Liu et al., 2017) and, thus, did not indicate practically significant measurement non-invariance across the three waves.

Table S2.

Discrepancies in Predicted Probabilities Based on Scalar Invariance Versus Metric Invariance Models

	Response category (degree of agreement)			
Indicator	totally disagree	disagree	agree	totally agree
Wave 1 (2012)				
Item 1	-.005	-.008	.018	-.004
Item 2	-.008	-.003	.041	-.029
Item 3	-.001	.002	.018	-.019
Wave 2 (2014)				
Item 1	.004	.008	-.003	-.008
Item 2	-.001	-.011	.005	.006
Item 3	.002	-.002	-.012	.012
Wave 3 (2017)				
Item 1	.001	.006	-.014	.006
Item 2	.005	.003	-.018	.010
Item 3	-.001	.004	-.005	.002

Note. Values greater than .05 are considered as practical significant.

Measurement invariance across the 27 European countries was examined using a factor analysis alignment approach for ordered-categorical data (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2014). This represents an extension of the multi-group confirmatory framework that is applicable for many groups. As the number of groups increases, it is often impossible to achieve full measurement invariance (e.g., Davidov, Meuleman, Cieciuch, Schmidt, &Billiet, 2014). However, prevalent approaches to identify partial measurement invariance become increasingly cumbersome and, more importantly, error prone with more groups and, typically, do not guarantee unbiased means (Marsh et al, 2017). Therefore, the alignment method aims at identifying approximate measurement invariance by trying to discover the most optimal measurement invariant model that keeps the degree of non-invariance to a minimum. Simulation studies indicate that as long as more than 25% of the parameters are invariant, mean comparisons are largely unbiased (Muthén & Asparouhov, 2014). Moreover, Monte Carlo simulations using the estimated parameters in a study can be carried out to determine how well the factor means are captured. If the estimated values of the alignment approach and the simulated factor parameters show a near perfect correlations (i.e., greater than .98), the ordering of the groups with respect to the factor means is trustworthy, even in the presence of a large number of non-invariant parameters (Muthén & Asparouhov, 2014). Therefore, we examined approximate measurement invariance of the attitude scale across the 27 countries using the factor alignment method. Again, we specified a single latent factor with three items and identified the latent factors by constraining the loading of the second item to 1. To account for the clustering of respondents within different measurement waves cluster-robust standard errors were estimated (Cameron & Miller, 2015). The results of the measurement invariance test are summarized in Table S3. About 7% of the factor loadings showed non-invariance; thus, approximate metric invariance was supported. Regarding the thresholds, about 25% of these parameters exhibited non-invariance. The non-invariance of the thresholds was primarily related to thresholds 2 and 3 of the third item; thus, Item 3 functioned somewhat differently across countries. To examine whether this affected the ordering of countries on the factor means, we conducted a Monte Carlo simulation using 100 replications following Muthén and Asparouhov (2014). The simulation showed a good coverage of the latent factor means (around .95) for most countries (see Table S4). More importantly, the correlation between the estimated factor means from our alignment analyses and the simulated factor means showed a near perfect correlation of r = .994. This indicates that the observed non-invariance of some parameters had a negligible effect on the ordering of the countries using the factor means and the attitude scale allowed for valid cross-country comparisons.

Table S3.

Invariance Results for Aligned Parameters.

Parameter	Country
Item 1	
Loading	**(1)** **(2)** 3 4 5 **(6)** 7 8 9 10 11 12 13 15 16 17 18 19 20 21 22 23 24 25 26 27 28
Threshold 1	**(1)** 2 3 4 5 6 7 8 9 **(10)** 11 12 **(13)** **(15)** 16 17 18 19 **(20)** 21 **(22)** 23 24 **(25)** **(26)** 27 28
Threshold 2	1 2 3 4 5 **(6)** **(7)** 8 9 10 11 **(12)** 13 15 16 17 18 19 20 21 **(22)** 23 **(24)** 25 26 27 28
Threshold 3	1 2 3 4 5 6 7 8 **(9)** **(10)** 11 **(12)** 13 **(15)** **(16)** 17 18 19 20 21 22 23 **(24)** **(25)** 26 27 28
Item 2	
Loading	1 2 3 4 5 **(6)** 7 8 9 10 11 12 13 15 16 17 18 19 20 21 22 23 24 25 26 27 28
Threshold 1	1 **(2)** 3 4 5 6 7 8 9 10 11 12 13 15 16 17 18 19 20 21 22 **(23)** 24 25 26 27 **(28)**
Threshold 2	1 2 3 4 5 6 7 8 9 10 11 12 13 15 16 17 18 19 20 21 **(22)** 23 24 **(25)** 26 **(27)** 28
Threshold 3	**(1)** **(2)** 3 4 5 6 7 8 **(9)** 10 11 12 13 **(15)** 16 17 18 19 20 **(21)** 22 23 24 25 26 27 28
Item 3	
Loading	1 2 3 4 5 6 **(7)** 8 9 10 11 12 13 15 16 17 18 19 20 21 **(22)** 23 24 25 26 27 28
Threshold 1	1 2 3 4 5 6 7 8 9 10 11 **(12)** **(13)** 15 16 17 18 19 20 21 22 23 24 25 26 27 **(28)**
Threshold 2	1 2 3 **(4)** 5 **(6)** 7 8 9 **(10)** 11 **(12)** **(13)** 15 16 **(17)** 18 **(19)** **(20)** 21 22 **(23)** 24 **(25)** **(26)** **(27)** 28
Threshold 3	**(1)** 2 3 **(4)** **(5)** 6 **(7)** **(8)** 9 10 **(11)** 12 13 15 16 **(17)** 18 **(19)** **(20)** 21 22 **(23)** **(24)** 25 **(26)** **(27)** **(28)**

Note. The numbers in parentheses refer to countries that show significant non-invariance for the parameter. The numbers for the countries were: 1 = Austria, 2 = Belgium, 3 = Bulgaria, 4= Cyprus, 5 = Czech Republic, 6 = Germany, 7 = Denmark, 8= Estonia, 9 = Spain, 10 = Finland, 11 = France, 12 = Great Britain, 13 = Greece, 15 = Hungary, 16 = Ireland, 17 = Italy, 18 = Lithuania, 19 = Luxembourg, 20 = Latvia, 21 = Malta, 22 = Netherlands, 23 = Poland, 24 = Portugal, 25 = Romania, 26 = Sweden, 27 = Slovenia, 28 = Slovakia.

Table S4.

Monte Carlo Simulation of Alignment: True Values, Estimates, and Coverage.

	True value	Estimates	Coverage
Austria	0.460	0.45	0.87
Belgium	0.404	0.40	0.92
Bulgaria	0.996	1.00	0.97
Cyprus	0.134	0.14	0.97
Czech Republic	0.891	0.87	0.94
Germany	0.536	0.53	0.98
Denmark	0.871	0.86	0.97
Estonia	0.809	0.80	0.95
Spain	0.378	0.38	0.94
Finland	0.659	0.65	0.93
France	0.193	0.19	0.96
Great Britain	0.437	0.43	0.92
Hungary	0.300	0.30	0.94
Ireland	0.429	0.43	0.96
Italy	0.439	0.43	0.92
Lithuania	0.717	0.71	0.96
Luxembourg	0.332	0.33	0.93
Latvia	0.722	0.70	0.91
Malta	0.284	0.290	0.94
Netherlands	0.667	0.66	0.95
Poland	0.770	0.76	0.97
Portugal	0.375	0.36	0.95
Romania	0.487	0.46	0.92
Sweden	1.003	0.98	0.95
Slovenia	0.566	0.55	0.93
Slovakia	1.206	1.20	0.92

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