Int J of Soc Robotics
DOI 10.1007/s12369-017-0401-3

Fear of Autonomous Robots and Artificial Intelligence: Evidence from National Representative Data with Probability Sampling

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Accepted: 28 February 2017

Abstract People vary in the extent to which they report fear toward robots, especially when they perceive that the robot is autonomous or has artificial intelligence. This research examines a specific form of sociological fear, which we name as fear of autonomous robots and artificial intelligence (FARAI). This fear may serve to affect how people will respond to and interact with robots. Applying data from a nationally representative dataset with probability sampling ($N = 1541$), research questions examine (1) the extent and frequency of FARAI, (2) demographic and media exposure predictors, and (3) correlates with other types of fear (i.e., loneliness, drones, and unemployment). A latent class analysis reveals that approximately 26% of participants reported experiencing a heightened level of FARAI. Demographic analyses show that FARAI is connected to participant sex, age, education, and household income; albeit these effects were small. Media exposure to science fiction predicts FARAI above and beyond the demographic variables. Correlational results indicate that FARAI is associated with other types of fear, including loneliness, becoming unemployed, and drone use. In sum, these findings render a much needed glimpse and update regarding how much individuals fear robots and artificial intelligence.

Keywords Fear · Autonomous robots · Artificial intelligence · Survey · National sample

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1 Introduction

As robots inevitably begin to enter various co-roboting contexts such as health, domestic, industry, and military areas, the need to understand how people perceive and anticipate interaction with robots is becoming increasingly crucial. Indeed, past research showed that people differ in their attitude toward robots [8]. In this study, we examined fear of robots and artificial intelligence based on the fear concept's sociological characteristics and its ability to elicit strong emotional responses [11].

We advance fear of autonomous robots and artificial intelligence (FARAI) as a novel concept to understand people's generalized anticipation of human–robot interaction (HRI). Clearly, autonomous robots and artificial intelligence are not the same at a conceptual or technical level. Conceivably, the general US population may not able to offer a clear distinction in similar way as roboticists and computer scientists. Our data (explained more in detail in the Sect. 5) support the contention that people do respond to autonomous robots and artificial intelligences in an empirically indistinguishable way. Thus, FARAI corresponds to the likelihood that individuals anticipate experiencing a higher magnitude of negative experience (i.e., to the point where they anticipate being fearful) when interacting with an autonomous robot and/or artificial intelligence.

As the first study of its kind to utilize a survey-based probability sample of the US population, this research aims to uncover the characteristics of people who experience FARAI. In particular, we outline three specific goals. The first goal is to provide an unprecedented descriptive basis (e.g., the extent to which the population may be estimated to have FARAI). This goal is useful in estimating the prevalence of such a fear. In addition, factor analytic strategies yield the

Published online: 08 March 2017

self-report items that form an empirical concept of FARAI. These survey items can be utilized in future work to assess and measure FARAI. The second goal is to explore and understand the sociological connections to FARAI. In particular, we examined demographics and the effect of communication (i.e., media exposure to science fiction) as predictors for FARAI. The purpose is to identify the characteristics of people and the effect of media exposure that lead to them reporting more or less fear. The third goal is to examine FARAI's connection to other types of fears (e.g., drones, loneliness, and unemployment). These correlations yield insight into other fears that people may have when experiencing FARAI, offering future researchers a way to possibly address FARAI.

2 Literature Review

In a seminal article, Tudor described fear as the sociological response to an anticipated stimulus (e.g., robots and AI) [11]. Although the actual fear that one experiences is generated contextually, an understanding or anticipation of fear follows sociocultural construction towards the fear object. Applied to HRI, the sociological construction toward autonomous robots and artificial intelligence may relate to the way people socially construct their understanding of robots and artificial intelligence. In other words, FARAI assesses the preconceived and strong emotional response that people anticipate in a prospective human–robot interaction.

Self-reported FARAI is also important in determining how people may react to the actual robot messages when such interactions do take place. The extended parallel processing model proposes that messages eliciting fear have the potential to lead individuals to engage in maladaptive responses [15]. These type of responses lower the quality of HRI. In addition, such a fear may lower perceived self-efficacy preceding HRI, therefore weakening the likelihood of a successful adoption of the robotic technology [13]. Given these arguments, FARAI serves as a good proxy of highly anticipated negative reaction toward robots.

Prior research in HRI has examined and developed a measure of negative attitude toward robots [8]. The current research distinguishes from these prior work by focusing on fear, which we explained to be a stronger sociologically-based response to anticipated HRI. Compared to attitude, fear is a stronger and more emotionally-based anticipation. Therefore, FARAI may have stronger effects predicting HRI outcomes. In addition, we focus on robots that are autonomous or conceived to have some artificial intelligence, instead of pre-programmed or tele-operated robots. Given the emergence of robot autonomy, the current research is essential for providing a descriptive basis of US population's negative dispositions toward robot autonomy.

3 Research Question

Given the rationales advanced, the first RQ explores the extent of the fear in the US population.

RQ 1 *To what extent do individuals in the United States report fear toward autonomous robots?*

The second goal is to examine demographics and communication predictors of FARAI. We examined demographics, in terms of sex, age, education, household income, and employment status on FARAI. These predictors offer description regarding the type of people who experience FARAI.

RQ 2 *How do demographic variables (i.e., gender, age, education, household income, and current employment status) influence fear toward autonomous robots and artificial intelligence?*

Communication predictors involved mass media exposure, especially to science fiction. This type of media exposure is likely to shape individuals' FARAI. A large body of work in media psychology points to how individuals selectively expose themselves to information in media (for a review, see [16]). Certainly, exposure to certain media, particularly science fiction, may amplify the realism of robot autonomy and artificial intelligence, associating these qualities with fear. Science fiction films, ranging from classics such as *2001: A Space Odyssey* and *The Terminator* to recent movies such as *Chappie* and *Deux Ex Machina* highlight the salience of autonomous robots and artificial intelligence such that they increase fear.

RQ 3 *What is the relationship between individuals' exposure to science fiction and fear toward autonomous robots and artificial intelligence?*

The last goal is to examine the correlates of FARAI with other types of fear. We focused on drone use, loneliness, and unemployment. In terms of loneliness, one possibility is that individual's own psychological state and need for belongingness (e.g., loneliness) affect their FARAI. Conceivably, persons who have a stronger social-based need may view robots as a potential threat to their own social connections with other people, and correspondingly regard robots more fearfully. Although drones are mostly controlled remotely by a human operator, they may provide the appearance of an autonomous robotic technology to the general population. Therefore, the extent to which they relate to FARAI yields insight regarding how non-autonomous technologies may be construed with autonomous robots and artificial intelligence. Lastly, robots provide some legitimate threat to job displacement, especially for many labor-intensive and service-based sectors [10]. Therefore, FARAI may be related to a fear for work displacement through unemployment:

RQ 4 *What is the relationship between fear of autonomous robot and artificial intelligence, and fears of loneliness, use of drones, and unemployment?*

4 Method

4.1 Data Collection and Probability Sampling

The data originated from the Chapman Survey of American Fears, Wave 2. Collected in 2015, it is part of an annual survey project. The survey's primary focus is asking questions designed to determine the extent to which Americans fear or worry about life events, governmental policy, crime and victimization, natural and man-made disasters, different spaces and a host of other phenomena. Particular survey items and response ranges were included to assess fear toward autonomous robots.

The data were collected by Knowledge Networks (http://www.knowledgenetworks.com/), a consumer research company with expertise in probability samples. The survey was designed to be representative of the general population with an initial panel recruited using random-digit-dialing, but is maintained using the US Postal Service's Delivery Sequence File that includes households without wired telephones. Selected households are invited to participate in a Web-based panel study. Panelists (2660) were recruited to take the survey via an email from Knowledge Networks. The survey was fielded from May 15, 2015 to May 26, 2015. Of the 2660 panelists recruited, 1541 ultimately completed the survey, for a completion rate of 58%. Thus, the final sample consists of 1541 non-institutionalized adults (18+ years old) who reside in the United States. The results reported in this research are weighed by the demographic characteristics in order to properly represent the adult population of the US. The demographic characteristics used for weighting included gender, age, race/ethnicity, education, region, household income, Internet access, etc.

4.2 Measurement

Participants were asked the extent to which they were fearful of autonomous robots and artificial intelligence on a four-point measure ranging from not afraid (1), slightly afraid (2), afraid (3), to very afraid (4). This Likert-type measure was similar to that of Fear Survey Schedule (FSS-II) [4]. The question asked "How afraid are you of the following?" and the items included: "Robots that can make their own decisions and take their own actions," "Robots replacing people in the workforce," "Artificial intelligence," and "People trusting artificial intelligence to do work."

In order to determine the underlying factor structure, the four items of FARAI were subjected to an exploratory factor analysis (EFA), using a maximum-likelihood factor extraction method with direct oblimin rotation. A maximum-likelihood extraction was chosen over a conventional principal-components extraction method, as it allows for the comparison of various fit indices and the significance test of factor loadings [3]. Similarly, an oblique rotation was chosen over an orthogonal rotation method (e.g., varimax), as the two constructs (i.e., fear of autonomous robots and fear of artificial intelligence) were expected to be highly correlated [9].

To ensure the suitability of the data for EFA, the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were examined. The KMO measure of sampling adequacy was .84 and the Bartlett's test of sphericity was also found significant ($p < .001$).

Zero-order correlations among the items ranged from .68 to .85. The examination of eigenvalues [5] reported one factor with eigenvalues >1.0, explaining 81.91% of the scale variance. The items yielded factor loadings ranging from .81 to .95. The scree test also revealed a clear break after the first factor [17]. Therefore, the data supported a one-factor solution. The Cronbach's alpha reliability for the four-item scale of FARAI was .93.

Media exposure to science fiction was measured with a single-item, seven-point measure ranging from never (1) to very often (7) regarding the frequency to which they watched television shows and movies related to science fiction, fantasy, superheroes, vampires, and zombies. Other types of fear, including loneliness, becoming unemployed, and drone use, were measured using single item measures ranging from not afraid (1), slightly afraid (2), afraid (3), to very afraid (4).

5 Results

To examine RQ1, a latent class analysis (LCA) was performed using Mplus [7] to identify the groups of individuals based on their level of fear. To examine RQ2 and RQ3, a hierarchical multiple regression analysis was conducted using IBM SPSS.

5.1 RQ1: General Fear Toward Autonomous Robots and Artificial Intelligence

Of the 1541 panelists completed the survey, 52 did not answer the questions related FARAI, making the final sample size 1489. On the scale of 1–4, 28.4% reported no fear (FARAI = 1), 40.3% reported between no fear and being slightly afraid ($1 <$ FARAI ≤ 2), 20.1% reported between being slight afraid and afraid ($2 <$ FARAI ≤ 3), and 18.5% reported between being afraid and vey afraid ($3 <$ FARAI ≤ 4). The average of all sample was 1.93 ($SD = .90$).

Table 1 Fit indices of LCA models on FARAI

Number of classes	AIC	BIC	ABIC	Entropy	LMR LR test p value	ALMR LR test p value
Two-class	3602	3623	3610	.849	<.0001	<.0001
Three-class	3485	3516	3497	.835	.0005	.0007
Four-class	2988	3031	3005	.938	<.0001	<.0001
Five-class	2992	3045	3014	.946	<.0001	<.0001
Six-class	2996	3060	3022	.750	.5083	.5083

Table 2 Regression analysis on fear of autonomous robots and artificial intelligence

Predictors	B	$SE\ B$	β	t	p
1st Block					
Gender	.133	.046	.074	2.876	.004
Age	.003	.001	.055	2.061	.040
Education	−.102	.025	−.114	−4.075	<.001
Household income	−.109	.051	−.059	−2.147	.032
Employment status	−.027	.052	−.015	−.522	.602
2nd Block					
Gender	.138	.046	.076	2.997	.003
Age	.004	.001	.068	2.486	.013
Education	−.102	.025	−.113	−4.075	<.001
Household income	−.103	.051	−.056	−2.030	.043
Employment status	−.030	.051	−.017	−.591	.555
Science fiction	.026	.011	.063	2.427	.015

An LCA was conducted on FARAI with two- to six-class models. Multiple model fit statistics and indices were considered together to determine the optimal number of classes [14]. Smaller values of Akaike's information criterion (AIC), Bayesian information criteria parsimony index (BIC), and sample-size adjusted Bayesian information criteria parsimony index (ABIC) indicated better model fits. For Lo-Mendell–Rubin likelihood-ratio test (LMR LR test), and Adjusted Lo-Mendell–Rubin likelihood-ratio test (ALMR LR test), the significant p value ($<.05$) indicated the model fit improvement from adding an additional class. An entropy value approaching to 1.0 indicated clear delineation of classes [2].

The results of the LCA indicated that a four-class solution was adequate. As shown in Table 1, the values of AIC, BIC and ABIC decreased each time the number of latent classes were added until it reached four. The level of entropy was adequate for all models, except the six-class model. The five-class model had the highest level of entropy and the p values of the LMR LR and ALMR LR tests were significant. However, it had higher values of AIC, BIC and ABIC compared to the four-class model and also yielded a class with zero latent class membership. Therefore, the four-class model was accepted as the optimal model.

The first class (44.0% of the sample) represented individuals who are not afraid of autonomous robots or artificial intelligence ($M = 1.12$). The second class (30.0%) represented individuals who are slightly afraid of autonomous robots and artificial intelligence ($M = 1.98$). The third class (16.5%) represented individuals who are afraid of autonomous robots and artificial intelligence ($M = 2.88$). The fourth class (9.5%) represented individuals who are very afraid of afraid of autonomous robots and artificial intelligence ($M = 3.85$). Based on these results, a cut-off score of 2.5 on the FARAI scale is adequate for identifying individuals who fear autonomous robots and artificial intelligence (26% of the sample).

5.2 RQ2: Influence of Demographic Variables

All statistical assumptions were checked prior to the regression analysis. The correlations among the predictors were low, ranging from −.27 to .28. The predictors had variance inflation factors (VIF) ranging from 1.01 to 1.21, indicating no serious threat concerning multicollinearity. An examination of residuals indicated no violations of statistical assumptions. To explore the influence of demographic variables, five major variables (gender, age, education, household income, and current employment status) were entered into the first block of a linear regression model. The overall model was significant, $F(5, 1479) = 8.82$, $p < .001$, adjusted $R^2 = .026$. All demographic variables except current employment status were significant predictors of FARAI (Table 2).

Females reported a higher level of fear ($M = 1.99$, $SD = .91$) than males ($M = 1.85$, $SD = .89$). Age was a significant and positive predictor of FARAI, $r(1539) = .05$, $p = .03$. Education was a significant and negative predictor of FARAI. An additional post-hoc analysis using Tukey's HSD showed that participants with a Bachelor's degree or higher ($M = 1.75$, $SD = .79$) had a lower level of fear compared to participants with some college ($M = 1.92$, $SD = .89$), high school ($M = 2.06$, $SD = .94$), or less than high school education ($M = 2.04$, $SD = 1.00$), $F(3, 1485) = 10.02$, $p < .001$. Household income was a significant and negative predictor of FARAI. Participants with household income under \$50,000, which approximates the US median household income [12], reported a higher level of fear ($M = 2.04$, $SD = .95$) than did those with household income of \$50,000 or above ($M = 1.85$, $SD = .86$), $t(1181.23) = 3.76$, $p < .001$. Finally, employment status was not a significant predictor of FARAI. Unemployed participants tended to report a higher level of fear ($M = 1.98$, $SD = .91$) than currently employed participants did ($M = 1.89$, $SD = .89$). However, the difference was not statistically significant.

5.3 RQ3: Exposure to Science Fiction

To examine the influence of individual's exposure to science fiction on fear of autonomous robots and artificial intelligence, media exposure to science fiction was entered into the second block (Table 2). With the demographic variables in the first block, the predictor in the second block was significant, $F_{change}(1, 1478) = 5.89$, $p = .02$, $R^2_{change} = .004$. Media exposure was a significant and positive predictor of FARAI, $r(1487) = .06$, $p = .03$. Individuals who watch science fiction movies were more likely to be afraid of autonomous robots and artificial intelligence, although the strength of association was modest.

5.4 RQ4: Relationship with Other Types of Fear

To examine the relationship between FARAI and other types of fear, zero-order correlations among the variables were examined. The results showed that FARAI was positively correlated with the fear of loneliness, $r(1480) = .25$, $p < .001$, as well as the fear of becoming unemployed, $r(1477) = .23$, $p < .001$. Similarly, FARAI was positively correlated with the fear of drone use, $r(1474) = .36$, $p < .001$. Additional analysis revealed that the influence of demographic variables on other types of fear was somewhat different from that on FARAI. For instance, while age was positively correlated with FARAI ($r = .05$, $p = .04$), it was negatively correlated with the fear of loneliness ($r = -.13$, $p < .001$) or unemployment ($r = -.33$, $p < .001$). Education was significantly associated with FARAI ($r = -.13$, $p < .001$), but not with the fear of unemployment ($r = -.02$, $p = .50$) or drone use ($r = -.04$, $p = .12$). Employment status was not a significant predictor of FARAI ($r = .05$, $p = .06$), but it was significant for the fear of loneliness ($r = .07$, $p = .01$), unemployment ($r = -.19$, $p < .001$), or drone use ($r = .06$, $p = .04$). Similar discrepancies were found for gender and household income, suggesting that FARAI is a somewhat related, yet distinct construct from other types of fear.

6 Discussion

The data and results rendered an interesting picture regarding people's fear toward autonomous robots and artificial intelligence. To start, the factor analysis allowed a population-level inference that individuals in the United States do not discern among their fear of robots or fear of artificial intelligence. Although roboticists and other specialists can clearly understand the conceptual distinction, the current findings suggest that such a distinction is less relevant to the general population.

The frequency of people who reported experiencing FARAI is actually quite surprising and prevalent. Using probability sampling, the results showed that almost one out of four US individuals reported experiencing FARAI. These results are particularly interesting considering that most people have not actually interacted with a robot, and yet, they already anticipate fearing an autonomous robot and artificial intelligence. These results inform prospective implementations of robots in new contexts. Specifically, such implementations should consider that people do experience fear. One possibility is to utilize the four-item measure for FARAI to assess prospective human operators or partners in order to establish a baseline for these people who are afraid of robots. Although this research does not examine possible intervention strategies to alleviate and address fear, people's fear should be considered in the implementation strategy. An encouraging line of research examines the effect of pre-interactional messages on HRI [6]. The authors found that exposing participants to online reviews about a robot from other human users can drastically alter the relationship between trust and interactional outcomes in a favorable direction. Perhaps these types of messages can be strategically disseminated in the face of FARAI.

Results also showed some demographic connections to FARAI. These results may not be surprising, however, they provide some additional considerations for new robot deployments. In particular, if the demographics overlap with those found in this study to have a higher level of FARAI: older persons, females, and individuals with lower education and lower income. It is possible that those people are more concerned about job displacement as a result of autonomous robots and artificial intelligence technology. As robots increasingly displace human employment, the existing income gaps between the young and the old, males and females, high-skilled workers and low-skilled workers, as well as upper class and middle class may widen. However, caution should be emphasized when interpreting these results. Moreover, the effects observed in the correlational model were small, indicating that the demographics served only as weak predictors of FARAI.

Interestingly, communication exposure to media related to science fiction uniquely predicted FARAI. This points to the fact that media exposure can influence how people regard robots. Specifically, increased exposure is associated with increased FARAI. These results also carry some indirect implications for the ways robots are portrayed in science fiction. However, not all segments of the sample did consume mass media and therefore were not exposed to the science fiction genre.

The last set of findings demonstrate associations between FARAI and fear of drones, loneliness, and unemployment. These findings were all correlational in nature, however, the effects were substantial. The findings related to drones suggest that a majority of the US population may not discern between drones and robotic technology. They may be simply afraid of the autonomy and the automation process. They may even simply regard FARAI as a category of technologies they do not understand, thus, fearing them in a similar direction. Conceivably, robotic technology and engineering may be difficult for most people to comprehend without an engineering or computer science background. However, interaction with more user-friendly applications (e.g., Lego Mindstorm and G15KS) may serve to reduce FARAI. The last two fear correlations, loneliness and unemployment are related to the possibility of robots displacing another person. Loneliness relates to a social displacement such that robots may eventually replace the traditional interpersonal connections that people have with each other. The relationship between FARAI and unemployment relates to a more practical fear of losing work to robots. Such a discussion is commonplace in the popular media. The results show that both of these fears connect similarly to robot fear, suggesting that future endeavors to reduce FARAI may involve addressing the social and employment aspects of robot implementation.

Future studies may also explore a phobia of robots. For people who report a high level of FARAI, their fear may progress into a phobia. According to the DSM-5 criteria, people have a specific phobia disorder when they experience significant and persistent fear when in the presence of, or anticipating the presence of the object of fear [1]. To be diagnosed as a specific phobia, the object (in this case, a robot) should almost always provokes immediate fear, which is out of proportion to the actual danger and causes substantial distress or impairment in social, occupational, or other important areas of functioning. No empirical research has so far documented an actual case of robophobia; however, as robots and artificial intelligence permeate wide segments of daily life, we can speculate its emergence in the future.

In conclusion, this research provided an important description of FARAI. Future work may examine how to minimize FARAI and if another national dataset is collected to ascertain and compare year–year results.

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