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Beyond Dirty, Dangerous and Dull: What Everyday People Think Robots Should Do

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ABSTRACT
We present a study of people's attitudes toward robot workers, identifying the characteristics of occupations for which people believe robots are qualified and desired. We deployed a web-based public-opinion survey that asked respondents (*n=250)* about their attitudes regarding robots' suitability for a variety of jobs (*n*=812) from the U.S. Department of Labor's O*NET occupational information database. We found that public opinion favors robots for jobs that require memorization, keen perceptual abilities, and service-orientation. People are preferred for occupations that require artistry, evaluation, judgment and diplomacy. In addition, we found that people will feel more positively toward robots doing jobs *with* people rather than *in place of* people.

Categories and Subject Descriptors
H5.2. Information interfaces and presentation (e.g., HCI): User Interfaces.

General Terms
Design, Human Factors

Keywords
Human-robot interaction, HRI, robots, occupations, jobs, survey

1. INTRODUCTION
A key motivation for creating robots is to eliminate the need for people to perform unattractive jobs. Indeed, the name "robot" is derived from the Czech *robota*, which means "compulsory labor" [5]. Robots are frequently envisioned as fulfilling jobs that have the three Ds: dirty, dangerous and dull. In this model, the archetypical robot job is repetitive physical labor on a steaming hot factory floor involving heavy machinery that threatens life and limb [26]. In the popular imagination, future examples along these lines include housework (Rosey in *The Jetsons*) and military activity or law enforcement (e.g., *Terminator*).

A contrasting perspective suggests that robots should be deployed in occupations that require vigilance, responsibility, and consistency. These include personal assistants (C3PO in *Star Wars*), caretakers (Teddy in *AI*), detectives (Daneel Olivaw in Asimov's *Caves of Steel*), and maternal figures (the mothership in *Alien*).

A third view suggests that robots should or could occupy *any* traditional human occupation, with the decision about whether to place a person or a robot into a particular job a mere hiring decision. Whether this is a utopia (as predicted by Hans Moravec's *Mind Children*) or a dystopia (as depicted in Kurt Vonnegut's *Player Piano*) differs from writer to writer, but many imagine a certain inevitability as robots become equal to humans in every domain.

These viewpoints suggest three questions: 1) *Can* robots perform various occupations as well as humans?, 2) Regardless of capabilities, which occupations *should* robots be permitted to do?, and 3) Should certain occupations be solely human or solely robotic, or are there occupations that should be inhabited by both humans and robots?

The first question is *technical*; in a sense, one can only definitively answer this question by waiting for technology to unfold. The second and third questions are *social* and susceptible to vary with the cultural milieu of the time. People's decisions about the types of occupations they want robots to undertake and whether they want to share occupations with robots can be determined by. In this paper, we focus on the second question, which is *subjective*, depending on the norms of the community.

In one sense, questions about occupations *per se* are intractable: According to the *Dictionary of Occupational Titles* [26], there are over 12,000 different jobs in the United States, with new occupations appearing and disappearing frequently. However, if we think of occupations in terms of clusters of job characteristics, then one can ask the question about which *types* of jobs are appropriately (in a social sense) performed by robots along with or instead of people.

To address these questions, we present a study of people's attitudes toward robot workers, identifying the characteristics of occupations for which people believe robots are qualified and desired. We surveyed people's opinions of whether various jobs were more appropriate for robots or humans, and gauged how these opinions differed when the occupations were presented as being held by "*either* robots *or* people" or by "*both* robots *and* people."

To the extent that public acceptance towards robots might be wider, or just different than what robot researchers are aware of, studies such as this one might improve the robotics community's ability to match technology to opportunity. The opinions of everyday people about what types of occupations could and should be automated are critical to the field of human-robot interactions

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because popular sentiment shapes technology adoption [7] and because technologies are more usable if they take people's expectations into account [19]. In addition, a more sophisticated understanding of the dimensions that govern attitudes toward robot work is valuable for the domain of human-robot interaction: it can guide researchers to identify key dimensions in the field, help to define grand challenges in the area of human-robot interaction, and influence development of research roadmaps. As public perspectives on robotics evolve, the type of study presented here will serve as a useful benchmark of shifting attitudes to robots as a rich part of the workplace rather than mere performers of the dirty, dangerous, and dull.

1.1 RESEARCH DESCRIPTION

This study aimed to address these research questions:

1. What aspects of work do people perceive as being appropriate for robot workers?
2. How do people feel about robotic workers in relation to human workers?

To address these questions, we deployed a web-based public-opinion survey that asked respondents about their attitudes regarding robots' suitability for a variety of jobs from the U.S. Department of Labor's O*NET occupational information database. By using both polarizing and non-polarizing response anchors [2] in our questionnaire design (i.e. using questionnaires that featured "both robots and people" as the midpoint for the Likert scale versus "either robots or people"), we assessed how responses to these questions differed when robot workers were suggested to work alongside humans rather than to replace human workers. We subsequently used regression analysis to predict robot-appropriateness of occupations with standard attributes and characteristics defined and evaluated by O*NET analysts [[20]. This study treated "robots" as a general category, and did not seek to influence or to determine what category of robot the respondents assumed in their response.

2. RELATED WORK

2.1 Assessment of attitudes towards robots

This study was inspired by research on public attitudes towards computers performing different occupations. Nass et al. [15] asked a random sample of people whether computers could and should do different jobs. While there were some revealing trends in the results, the ad hoc selection of and interpretation of the occupation characteristics, the small number of occupations and responses, and the fact that the survey made references to computers while many of the occupations required physical tasks limits the conclusions that could be drawn.

While there is a significant body of work oriented towards assessing individual attitudes towards specific robots (e.g., Paro [22], Nursebot [13], Asimo [14] or Aibo [9]), or specific robot roles (for example, [8]), broader studies of public attitudes towards robots are more rare. Nomura et al. have developed the Negative Attitudes towards Robots Scale [17] to provide a benchmark with which to test attitudinal differences between different cultures and demographics. Studies using this scale focus on the social, emotional, and interactional attitudes people hold towards robots. However, those questions are very difficult to relate to aspects of robot occupations.

2.2 Measures of robots

Current measures for robots in the HRI literature can be roughly divided into two categories: task factors and social factors. Task factors are those where the intermediate metric of a robot's effectiveness is based on its job performance. These factors tend to be quantitative, objective measures of robot function. A solid overview of such metrics may be found in [23].

While social factors clearly affect the task-effectiveness of robots, particularly in collaborative or social service settings, these measures tend to differ from other task factors in that these factors are often subjective and attitudinal. Studies which focus on social factors will measure people's comfort with robots, their assessment of the human-likeness of robots [10], a robot's perceived communicative abilities [1], their emotions towards robots [4], their performance on joint tasks with robots [10], etc.

While the measures in the current study are subjective (consistent with the social measures) and performance-related (consistent with task measures), there are three differences between these types of measures and those used in the current study. First, rather than generating robot-specific measures, our study uses standard occupational measures that make it easier to compare people and robots. Our occupational taxonomy has been rigorously validated, independent of descriptions of robots. Second, we use aggregate application-based measures that can help to reveal holes in individual capability metrics. For instance, a psychologist robot may score well on individual task or social measures, by assuming human-like form and asking open-ended questions (a la Eliza), but few people would find this to be a reasonable alternative to a human psychologist [15]. Conversely, an aggregate measure can help highlight this difference and illuminate what additional factors are critical to occupational acceptance. Finally, our study uses indirect measures, employing regression analysis to draw out dimensions of complicated variables with non-expert respondents.

3. STUDY DESIGN

We used an online survey to poll people about what occupations robots could and should do. Our goals in this study were twofold. First, we aimed to identify key occupational dimensions influencing attitudes toward robots. Second, we addressed our research questions with two working hypotheses: (H1) People will feel more positively toward robots doing occupations *that people also do* rather than *replacing* people; (H2) People will differentiate between their attitudes about what occupations robots *could do* versus what they *should* do.

Our study also featured two manipulations between respondents. To test differences in response to collaborative vs. competitive human-robot work scenarios, half of the respondents had scales designed to suggest that jobs were performed by humans *or* robots, while the other half had scales that suggested jobs being performed by humans *and* robots. To address issues of ordering, we balanced the study so that half of the respondents saw robots on the left of their answer scales, and humans on the right, while the other half saw the reverse. The *and* vs. *or* manipulation was implemented as between-respondents. The *could* vs. *should* manipulation was implemented as within-respondents.

In our study, we did not specify to respondents what kind of robot to consider. While previous researchers [17] asked respondents to self-select which type of robot they were evaluating, many of the robot-form/occupation pairings would have been nonsensical. We drew from Thrun's observation [25] that a robot's key characteristic—its "kind"—derives directly from its occupational category (industrial, professional service or personal service). Thus, we surmised that respondents could reasonably consider the appropriate kind of robot for the job.

3.1 Respondents

All respondents were volunteers recruited from the public web site "Mechanical Turk" operated by Amazon.com [12], who selected the Human Intelligence Task (HIT) entitled "Attitudinal survey about jobs." A total of 250 people participated in the study: 133 women, 113 men, and 4 unknown. They represented a wide range of ages, from 18 to 77 years (*M*=32.8, *SD*=10.9), employment situations, and educational levels (see Figure 1). Respondent IP addresses indicated that they predominately came from industrialized countries. They had varied amounts of experience with robots; 86.7% had never owned a robot. When asked how familiar they were with robots, their responses ranged from 0="none at all" to 4="extremely", *M*=1.94, *SD*=0.80.

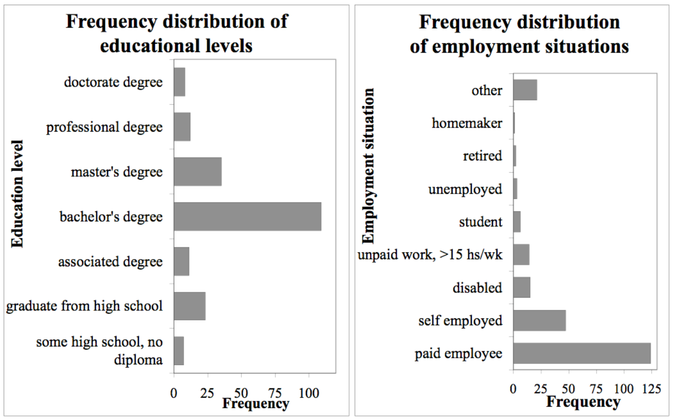


Figure 1. Distributions of respondent educational levels and employment situations

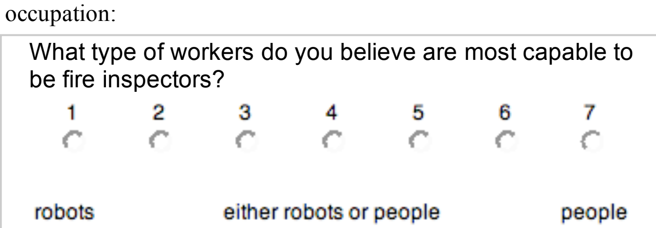
3.2 Materials

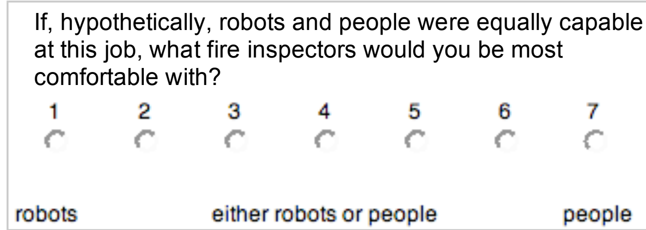
We used the O*NET database as our information resource for occupation names, descriptions, and ratings. O*NET is the database used by the U.S. Department of Labor in ongoing longitudinal surveys [20]. At the time we ran the study, we used the most recent database available (version 11). It contained 812 occupations that were scored within a hierarchical taxonomy of 277 descriptors.

We recruited respondents from the Mechanical Turk system to reach a broad sample of people and to lower the barriers to entry. Each respondent received $.05 for participation.

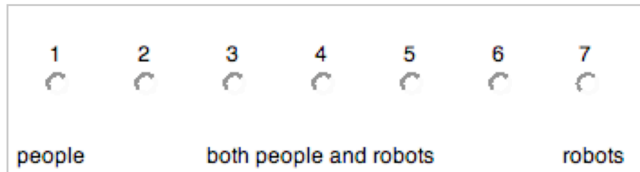
3.3 Procedure

The online survey contained 28 entries featuring 28 randomly selected occupations. Each entry consisted of an O*NET occupation name (e.g., "Fire inspectors"), the O*NET occupation description (e.g., Inspect building and equipment to detect fire hazards and enforce state and local regulations), and two questions about that occupation:





There were four possible wordings for the scale anchors — 2 (mid-point wording: AND vs. OR) x 2 (response word ordering: ROBOTS TO THE LEFT vs. PEOPLE TO THE LEFT) both between-respondents. The preceding example shows the OR + ROBOTS TO THE LEFT scale. The following example is from the AND + PEOPLE TO THE LEFT condition:



Demographic questions were included at the end of the questionnaire and are reported in Section 3.1.

3.4 Measures

The primary dependent variable was the seven-point scale rating. Because people's responses vary widely in such surveys, we used the median responses across respondents for each occupation to create a single median *could* and *should* rating for each occupation. This was done because: (1) median scores are more robust to outliers than means and (2) each respondent received a small random subset of the 812 occupations so we could not cleanly identify the source of variance (e.g., individual differences or differences caused by the particular subset of occupations). Because median scores were used as the primary dependent variable, as opposed to individual's scores, we were unable to include the individual demographic information as predictors in the data analyses.

4. ANALYSES

We took a variable-based approach [16] to identify the *underlying variables* of occupations that predict what people believe robots should do. This contrasts against an orientation toward identifying particular occupations that robots should do. These predictor variables were derived from the occupation descriptors in the O*NET database. The ten categories were: abilities, education, interests, job zones, knowledge, skills, work activities, work context, work styles, and work values.

Though forward stepwise regression is insufficient for analyzing theory-driven analyses, it is useful for an exploratory analysis such as this one [11], [24]. We ran two separate linear regression analyses. The first set of analyses selected the best predictors from within each of the O*NET descriptor categories. The second analysis characterized the relative effect of all of the individual predictors, irrespective of their category. In Step 1 of the regression analyses, we entered the dichotomous independent variables "and/or" and "could/should". In Step 2, we used stepwise selection of all other predictors.

As described in Section 3.4, the aggregated median score of responses to each of the O*NET occupations was used as the dependent variable in these regression analyses.

4.1 Calculating Predictor Factors

We combined the descriptors into robust indices from each of the O*NET sub-categories, e.g., the skills category had sub-categories of social, technical, resource management, etc. For each of these subcategories, we identified the descriptor items that covaried, using Principal Components Analysis, e.g., social skills consists of descriptors such as social perceptiveness, coordination, persuasion, negotiation, instructing, and service orientation skills. Then we created sub-category indices by calculating the unweighted average of the individual descriptors. Experts in the field did the ratings on the O*NET dimensions for each occupation. Only the questions in Section 3.3 were asked of respondents in the current study.

4.2 Interpreting Regression Analysis Results

4.2.1 Predictor Variables

Identifying significant predictors of attitudes toward robot work was of primary interest in the current study. Therefore, we report the significant and non-significant predictors for each model.

β values represent the standardized regression coefficients of the model: $Y = B + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \varepsilon$ (error). Because these coefficients are extremely sensitive to the particular predictors and accuracy of measures in the model [6], we only noted the direction (+/-) of the significant coefficients without drawing conclusions from the coefficient sizes. Negative regression coefficients indicate a preference for robots to do that type of occupation. Positive regression coefficients indicate a preference for people to do that type of occupation. Data from PEOPLE TO THE LEFT conditions were reverse-coded.

4.2.2 Regression Models

The R^2 value typically indicates the goodness-of-fit for a regression model; it represents the proportion of variance in the data that is predicted by the model, where 0 is none and 1 is all. Depending upon the complexity of the dependent variable and the noise in the predictors, different R^2 values are considered to be satisfactory. Given the diversity of respondents and public opinions, the predictive power (R^2) of each of these models is surprisingly high.

5. RESULTS AND DISCUSSION

5.1 And vs. Or Scale Wording (H1)

In every regression analysis in this study, we found that the collaborative vs. competitive (AND VS. OR) manipulation was a significant predictor of respondents' preferences regarding robot work. Hypothesis 1 was clearly supported that people will feel more positively toward robots doing jobs *with* people rather than *in place of* people. Methodologically, this indicates that simply using a different midpoint anchor can result in different attitudinal responses. This suggests that the midpoint anchor may trigger different conceptions of robot work, which result in more or less openness to robot workers (see Table 1, Column 4).

5.2 Could vs. Should Question Wording (H2)

This within-respondent variation of question wording was not a significant predictor in any of the regression models generated by this data set. Thus, Hypothesis 2 was not supported by this data. It is possible that follow-up studies in the future will attain different results, e.g., when people become more aware of robot capabilities, they may draw stronger distinctions between what robots could vs. should do (see Table 1, Column 3).

5.3 Regression Models for Each Category

The ten categories of occupational descriptors were used to examine key sub-categories within each occupational dimension category. The final regression models for these categories are reported in Table 1. As seen from the variance inflation factor (VIF) values in Table 1, none of these models suffer from multicollinearity. VIFs of 10 or greater are typically a sign of multicollinearity.

5.3.1 *Abilities*

This regression model of abilities highlights the significance of *Control Movement Abilities*, i.e., "abilities related to the control and manipulation of objects in time and space" [20], a highly reliable (Cronbach's α=.97) five-item index. Being an airline pilot requires excellent control movement abilities, while being a school counselor does not. Example occupations were selected from the extreme ends of the O*NET control movement abilities ratings. Its standardized coefficient (β) is negative, suggesting that robots are preferred for occupations that require control movement abilities. However, this does *not* mean that airline pilots should be robots and school counselors should not. Other dimensions of each occupation might make it more suitable for people. (See Table 1, Row A.)

5.3.2 Education and *Job Zones*

Because education and job zones were similar in scope, they were analyzed together. The regression analysis illuminated the significant predictor of *Related Work Experience*, i.e., "amount of related work experience required to get hired for the job" [20]. Computer systems analysts must have extensive related work experience, whereas crossing guard do not. The positive β suggests that respondents preferred that people do jobs that require previous related work experience. (See Table 1, Row B.)

5.3.3 Interests

Respondents preferred robots to do occupations that involved *Realistic Interests* i.e., "frequently involve work activities that include practical, hands-on problems and solutions" [20]. Plumbing is an example of an occupation involving realistic interests; financial and sales managements do not. The negative β suggests that respondents preferred robots to do occupations that involve realistic interests. (See Table 1, Row C.)

5.3.4 Knowledge

The regression analysis for knowledge types identified the significant predictors of *Business Management* and *Physical Sciences* knowledge. Business management is a highly reliable (α=.94) ten-item index that reflects "[k]nowledge of principles and facts related to business administration and accounting, human and material resource management in organizations, sales and marketing, economics, and office information and organizing systems" [20]. Financial management requires business management knowledge, while hunting requires virtually none. Occupations requiring business management knowledge were rated as more appropriate for people than robots.

Physical sciences knowledge was a highly reliable (α=.89) five-item index, involving knowledge of physics, chemistry, and biology. Being a hydrologist requires physical sciences knowledge; being a travel agent does not. Respondents preferred that robots for occupations that require extensive knowledge of physical sciences. (See Table 1, Row D.)

Table 1. Regression Models Generated for Each Category of Occupational Dimensions

	Full Model	Predictor Variables		
	(1) Model significance (F) and fit (R^2)	(2) Significant predictors (preference, β, VIF, example occupation)	(3) Other predictors (included in original model, but are *not* significant predictors)	(4) Significant Predictor And vs. Or
(A) Abilities	$F(3, 3164)=40.01$*** $R^2=.04$	**Control movements** prefer robots $\beta=-.06$***, VIF=1.00 e.g., airline pilots	• Could vs. should • Cognitive • Idea generation • Quantitative • Memorization • Perceptual • Spatial orientation • Attentiveness • Psychomotor • Reaction time • Physical • Stamina • Flexibility and balance • Visual • Auditory	$\beta=0.18$*** VIF=1.00
(B) Education & Job Zones	$F(3,2694)=34.40$*** $R^2=.04$	**Related work experience** prefer people $\beta=.06$**, VIF=1.00 e.g., computer systems analysts	• Could vs. should • On site training • On job training • Education level • Job zone	$\beta=0.18$*** VIF=1.00
(C) Interests	$F(3, 2966)=39.40$*** $R^2=.04$	**Realistic interests** prefer robots $\beta=-.07$***, VIF=1.00 e.g., plumbers	• Could vs. should • Artistic • Conventional • Enterprising • Investigative • Social	$\beta=.18$*** VIF=1.00
(D) Knowledge	$F(4,3163)=33.06$*** $R^2=.04$	**Business management** prefer people $\beta=.08$***, VIF=1.01 e.g., financial managers **Physical science** prefer robots $\beta=-.04$*, VIF=1.01 e.g., hydrologists	• Could vs. should • Production • Engineering tech • Social science • Health science • Education • Humanities • Public safety Communication	$\beta=.19$*** VIF=1.00
(E) Skills	$F(3,3164)=39.50$*** $R^2=.04$	**Social skills** prefer people $\beta=.06$**, VIF=1.00 e.g., psychiatrists	• Could vs. should • Math or science • Problem solving • Technical • Systems • Resource management	$\beta=.18$*** VIF=1.00
(F) Work Activities	$F(3, 3164)=41.20$*** $R^2=.04$	**Info data processing** prefer people $\beta=.07$***, VIF=1.00 e.g., auditors	• Could vs. should • Info input • Identify info • Reasoning • Physical work • Maintaining equipment • Documenting • Communication • Coordinating • Administrating	$\beta=.18$*** VIF=1.00
(G) Work Context	$F(3, 2694)=34.22$*** $R^2=.04$	**Communication** prefer people $\beta=.06$***, VIF=1.00 e.g., urban planners	• Could vs. should • Role relationship • Responsibility for others • Conflict contact • Physical work • Environmental conditions • Job hazards • Body positioning • Work attire • Criticality of position • Routine vs. challenging • Competition • Time pressure	$\beta=.18$*** VIF=1.00
(H) Work Styles	$F(3,2694)=33.49$*** $R^2=.04$	**Practical intelligence** prefer people $\beta=.06$**, VIF=1.00 e.g., health educators	• Could vs. should • Achievement orientation • Adjustment • Interpersonal orientation • Conscientiousness	$\beta=.14$*** VIF=1.00
(I) Work Values	$F(3,2966)=38.53$*** $R^2=.04$	**Working conditions** prefer people $\beta=.06$**, VIF=1.00 e.g., chief executives	• Could vs. should • Achievement • Recognition • Relationship • Support • Independence	$\beta=.18$*** VIF=1.00

*=$p<.05$ (significant at the .05 level), **=$p<.01$ (significant at the .01 level), ***=$p<.001$ (significant at the .001 level)

5.3.5 Skills

Social Skills was a very reliable (α=.97) 12-item index that involves "developed capacities used to work with people to achieve goals" [20], including social perceptiveness, coordination, instructing, negotiation, persuasion, and service orientation skills. Psychiatry requires strong social skills, while bookbinding does not. Respondents preferred people for occupations involving social skills. (See Table 1, Row E.)

5.3.6 Work Activities

Information and Data Processing was a highly reliable (α=.94) eight-item index that was a significant predictor among work activities. This involves using information to perform a job, including judging quality, compiling, coding, categorizing, evaluating, and analyzing data [20]. Auditors do lots of information and data processing, while music performers do not. Respondents preferred that people do such work activities. (See Table 1, Row F.)

5.3.7 Work Contexts

Within work contexts, *Communication* was a very reliable (α=.80) six-item index found to be the significant predictor for attitudes towards robots in human occupation. Communication describes the "[t]ypes and frequency of interactions with other people that are required as part of this job" [20]. Urban planning requires communication, while hand sewing does not. Those occupations that involve lots of communication were viewed as being more appropriate for people than robots. (See Table 1, Row G.)

5.3.8 Work Styles

Practical Intelligence was the only work style predictor that significantly predicted attitudes towards robots doing human occupations. Practical intelligence involves "generating useful ideas and thinking things through logically" [20]. Health education is an example of an occupation that requires practical intelligence; ushering and attending lobbies do not. Respondents preferred that people do jobs that require lots of practical intelligence rather than robots. (See Table 1, Row H.)

5.3.9 Work Values

The 3 Ds refer to work values. This regression analysis illuminated the issue of *Working Conditions*, a very reliable (α=.85) six-item index referring to "job security and good working conditions" [20]; corresponding needs are activity, compensation, security, and variety. Chief executives have very good working conditions; roofers do not. Respondents preferred that people do jobs with good working conditions rather than robots. (See Table 1, Row I.)

5.4 Regression Model with All Sub-Categories

To determine the overall predictors of attitudes toward robot work, we ran factors from all ten categories in a regression analysis. The final model included nine significant predictors as well as the AND VS. OR factor, $F(11,2488)$=14.35, p<.001, R^2=.06. "And vs. or" was once again a significant predictor in the same direction as previous analyses, β=0.19, p<.001, VIF=1.00. This model also did not suffer from multicollinearity.

5.4.1 Predictors of Robot-Appropriate Occupations

All factors included in the regression models in Table 1 were included in this analysis. The significant predictors that characterize robot-appropriate occupations are:

- Memorization (abilities) (very reliable two-item index, α=.89): The ability to remember information such as words, numbers, pictures, and procedures. Travel guides are an example of workers who require strong memorization abilities; painters are an example of workers who do not. β=-.06, p<.05, VIF=1.81
- Perceptual (abilities) (very reliable six-item index, α=.94): Abilities related to the acquisition and organization of visual information. Air-traffic controllers need keen perceptual abilities; models are low. β=-.07, p<.05, VIF=1.82.
- Realistic (interests) (single item): Realistic occupations frequently involve work activities that include practical, hands-on problems and solutions. They often deal with plants, animals, and real-world materials like wood, tools, and machinery. Many of the occupations require working outside, and do not involve much paperwork or working closely with others. Plumbers are high; financial and sales managers are low. β=-.11, p<.001, VIF=2.09.
- Humanities (knowledge) (single item): Knowledge of facts and principles related to the branches of learning concerned with human thought, language, and the arts. Archaeologists are high; biochemists are low. β=-.07, p<.01, VIF=1.75.
- Relationships (work values) (reliable three-item index, α=.79): Occupations that satisfy this work value allow employees to provide service to others and work with co-workers in a friendly non-competitive environment. Physical therapists are high; truck drivers are low. β=-.06, p<.05, VIF=1.76.

5.4.2 Predictors of People-Appropriate Occupations

The predictors that significantly indicate a preference for *people*-appropriate occupations are:

- Related work experience (education) (single item): Amount of related work experience required to get hired for the job. Computer systems analysts are high; crossing guards are low. β=.05, p<.05, VIF=1.19.
- Artistic (interests) (single item): Artistic occupations frequently involve working with forms, designs and patterns. They often require self-expression and the work can be done without following a clear set of rules. Industrial designers are high; electromechanical equipment assemblers are low. β=.05, p<.05, VIF=1.54.
- Identify and Evaluating Job-Relevant Information (work activities) (very reliable five-item index, α=.82): How is information interpreted to perform this job? Anesthesiologists are high; musicians and singers are low. β=.08, p<.01, VIF=1.70.
- Role relationships (work context) (reliable three-item index, α=.62): Importance of different types of interactions with others both inside and outside the organization. Producers and directors are high; tree trimmers and pruners are low. β=.06, p<.05, VIF=1.56.

6. CONCLUSIONS

In contrast to the simplistic notion that robots should do dangerous, dirty, and dull jobs, our analysis shows that public opinion favors robots for jobs that require memorization, keen perceptual skills, and service-orientation. People are preferred for occupations that require artistry, evaluation, judgment and diplomacy.

If one is concerned primarily with one particular category of occupational dimensions, then the analyses found in Table 1 presents those sub-categories of occupational dimensions that stand out as significant predictors of attitudes towards robots doing such jobs. As an example, if one were interested in occupational abilities and the types of occupations in which robots would be more acceptable to the public, then one would find that occupations requiring strong abilities in control movements would be well suited for robotic workers (Table 1, Row A).

Taken together, these findings indicate that occupational dimensions are significant predictors of attitudes toward the place of robots in the workforce. This was a test of the utility of applying standard human occupational scales to occupational assessment of robots. Going beyond the three Ds, these models illuminate other occupational dimensions that could be appropriate for robots.

This study supported our hypothesis (H1) that people would feel more positively toward robots doing occupations *with* people rather than *in place of* people. However, it did not support hypothesis (H2) that people would differentiate between their attitudes about what occupations robots *could* vs. *should* do.

The breadth of this sample makes it a powerful basis from which to draw conclusions. The focus on randomization and balancing in the design strengthens its validity and reliability. Limitations of the current study include those created by our data collection and analyses. First, this study would have targeted a more particular or broadly representative population if we had employed different recruitment methods. Second, regression models are subject to the vagaries of each predictor included in the model [6]. Therefore, we recommend further and multiple-method approaches to this subject area. Third, the O*NET occupational dimensions were rated by experts, but respondents were not experts on all of the occupations they saw. Future studies could focus on the publicly perceived occupational characteristics rather than expert judgments of occupational characteristics.

In addition, future studies could seek to identify other factors influencing differences in the responses to robot work. Whereas this study treated "robots" as a general category and drew inferences from the averaged response, a follow-up study could test the influence of different visions or assumptions of robot work on the perceived capability or suitability of robots for different kinds of work. Future studies could also build on past research on individual differences in technophobia [27] and assumptions and attitudes about robots [17], [18]. Though this study focused primarily upon Western countries, a specific study of cultural factors could be included in future studies with a particular interest in cultural similarities and differences in perceptions of the acceptability of robots doing various types of occupations. This study was intended to be a first step to test the effectiveness of using human occupational dimensions to make predictions about perceptions of robots. Further demographic factors such as occupation, age, gender, education, and socio-economic background would also be informative, particularly comparing robotics expert to public opinions.

Despite its limitations, this study provides the first step toward identifying important dimensions of occupations that predict preferences for robotic workers. These dimensions also provide a snapshot of what aspects of human work people seem to feel are uniquely human today. We often define humanness by contrasting people with current-day technologies [3]. Hence, an understanding of the lines people draw when thinking about occupations can provide insights into the more fundamental question of what people believe distinguishes humans from their technologies.

Most importantly, this study found that occupational dimensions are useful for human-robot interaction research for attitudes toward robot workers. It provides a benchmark against which to compare future studies of attitudes toward robot workers and affords insight for the human-robot interaction community to form goals for robot design and placement within the workforce.

7. REFERENCES

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