# Social Fit: What social goals people associate with robots and why?


Ozcan Ilikhan
Department of Computer Sciences
University of Wisconsin-Madison
ilikhan@cs.wisc.edu

Faisal Khan
Department of Computer Sciences
University of Wisconsin-Madison
faisal@cs.wisc.edu

Alex Moy
Department of Psychology and Computer Sciences
University of Wisconsin-Madison
amoy@cs.wisc.edu



## ABSTRACT

We are interested in user's expectations of social robotic assistants as it relates to a given context and task, namely how well does the assistant fit the task. Participants ($N$ = 42) were given an online survey with images including human, human-like robot, and machine-like robot assistants in various contexts i.e. home, office, and public settings. Participants then rated each assistant on how efficient they perceived it to be able to accomplish a task in the given context, how comfortable they were with the assistant performing the task in that context, how well the assistant fit the task and context, and whether they preferred the assistant for the task and context. Human assistants were found to be best suited for all tasks, and humanoid robot assistants were perceived to be better suited than machine-like robots in all socially interactive tasks.



## Categories and Subject Descriptors

## General Terms

Social Agents, Social Robots, Human-Computer Interaction

## Keywords


## 1. INTRODUCTION

Defining what constitutes a social robot has been a subject of academic debate in recent years. One view is that social robots are machines that have the ability to interact with living organisms. Later revisions included that robots must behave conductively, be able to communicate, collaborate, and coordinate with human users, and be autonomous. Bartneck's[1] definition serves as a good contemporary summary of a social robot:

> *A Social Robot is an autonomous motion device equipped with sensors, actuators, and interfaces that interacts and communicates with humans following some expected behavior rules, which are founded on the robot physical properties and the environment within it is embedded, mainly taking into account the needs of the people with which it is meant to interact with.*

Although this definition cannot be a general representation of what constitutes a social robot[1], it does provide us with a framework to motivate the needs for further study. In light of this description, a social robot's physical form and environment to which it is embedded ascribes to its behavior. This view of looking at social robots is consistent with another similar taxonomy done by Hegel et al [6], which argues that systematic links among a robot's form, function and context is crucial in developing models for deeper understanding of social aspects of these new forms of interfaces.

Thus far, a major focus of research regarding social robots is on improving robot's capabilities to improve its interaction with humans in a certain context. In other words, people have looked into what forms of robots are suitable in certain environments, but there is little work that looks at a holistic view of social robots by considering a robot's form, function and context together. A study by Casper [4] looked at different forms of robots used in search & rescue and highlighted different issues that arise due to interaction of rescue workers under stress with these robots. In addition, studies of robots in autism therapy [7] and elder care [8] have explored features of different robots and how they facilitate interaction among elderly and autistic persons. Likewise, similar studies have been done in other areas such as museums [3], homes [2], and collaboration [9] etc.

We recognize the importance of studies done on the appearance of robots and how they can effect their perception as concluded by Kiesler et al [5]. There is a strong need to better understand the expectation of people regarding different kinds of functions that they associate with robots. In this paper, we aim to investigate the matches among social goals, which we define as tasks robots are expected to achieve, social contexts, which are environments where these tasks are desirable, and form (or physical features) of robots.

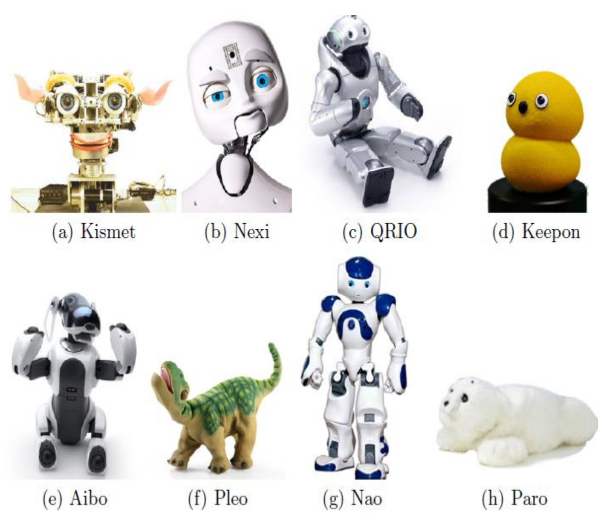



Figure 1: Social robots used in our study

[1] Given the novelty of this field, we can expect that no definition can encompass the whole social robot paradigm.

We conducted a semester long project that involved one exploratory study and one experimental study exploring the fit between robot appearance and different tasks and contexts. Here we present the design and results of both of our exploratory and experimental studies along with discussion of our findings. The rest of this report is organized as: section 2 looks at other work related to ours, design, results and discussion of our exploratory work is given in section 3, section 4 provides details on experimental phase of our project following by conclusion of our work in section 5.

## 2. RELATED WORK

The idea of understanding social robots within a holistic framework is fairly recent [6][10]. There is some work on how a robot's appearance and behavior affect people's perception of robots, their abilities, and their humanness. However, studies have neglected to explore the form, function and context as one unit.

Kiesler et al [8] performed a study on social robots related to matching robot appearance and behavior to tasks to improve human-robot cooperation. Results from the study supports a strong connection between a robot's appearance and people's perception of the robot. Our project can be considered as an extension of their work as we take into consideration robot appearance along with a task and a context.

Another study done by Riek et al [11] provided general guidelines for the design of humanoid robot heads. Their main argument was that rather than the body of the robot, the existence of certain features and dimensions of robot's faces most dramatically contributed to people's perception of its humanness. Their work is significantly different than ours, as they did not involve any specific task or context when evaluating the appearance of robots.

## 3. EXPLORATORY STUDY

The primary purpose of the exploratory phase of this project was to gain a broader understanding of different social goals that people expect of robots in certain social settings. We were interested in establishing match triplets of the form appearance-task-context. One simple example of a match could be to find out that a biped robot e.g. Asimo (appearance) is preferred in a shopping mall (context) doing a receptionist's job (task). Additionally, we wanted to encourage participants to think of tasks in their immediate surroundings that could be improved upon by robots. This study was as open-ended as possible so as to not restrict our participant's choice of context and tasks. Taking these requirements into consideration, we designed two sets of studies: (i) an open-ended diary handed out to a large set of participants (ii) interviewing the general population in a variety of settings.

### *3.1 Survey I - Cultural Probe*

This was an open-ended inquiry that involved handing out a small diary to all of our recruited participants. Participants were asked to keep these diaries for a one week time period. During this time they recorded any task, activity or chore in their environment for which a robot could provide better assistance. For all observations, they were asked to record (a) the task for which they are interested in getting robot assistance (b) the context or environment where the task in 'a' fits (c) robot appearance (form, features and functionalities) that are desirable for achieving 'a' (d) reasons for these three choices.

We prepared a custom-designed diary that included two side-by-side pages for a single observation. On the first page for each observation we also provide a representative set of robot images (different on each page) taken from the set of social robots (figure 1). Participants were free to choose any of these robots, but they were not restricted to only our compiled set of robots. We provided extra space on the second page of each observation to provide drawing or description of a suitable robot. Irrespective of whether they selected or drew a robot, they were encouraged to provide reasons for their selections.

***Participants*** -- We recruited 20 participants from the University of Wisconsin-Madison campus area; all were undergraduate and graduate students in either computer science or engineering. A small portion of our participants also had first-hand experience working with robots e.g. undergraduate students who participated in a robot design competition. However, the majority of our participants were largely unfamiliar with robots and robotic design. All participation in these studies was voluntary.

Figure 2: A few sample pages from our cultural probe. The empty boxes shown were used to describe the social goal and social context where this goal fits in, respectively.

### *3.2 Survey II - Contextual Inquiry*

A second contextual inquiry style survey was based on two sets of interviews. In one set of interviews, we sought to gain perceptions from the general public about the fit of a given set of robot pictures for a given task and context. The other set of interviews varied from the first set in that we sought to gain perceptions of participants about the fit of a given set of robot pictures in their immediate setting. That is, how well would a robot fit into their current environment. We predicted that the salience and immediacy of the setting would yield more vivid and concrete descriptions of participant's expectations.

***Participants*** -- Participants were recruited from different locations around campus to conduct these surveys. For the general contextual inquiry interviews, we asked people around a campus library and a shopping mall. For the context-immediate contextual inquiry survey, we visited a few shops in a frequently visited area of campus.

### *3.3 Results*

As our exploratory study was very open-ended, we had some initial difficulties in analyzing a very diverse set of responses from our three sets of surveys. The approach we finally adopted was to use an affinity-diagramming technique to iteratively group related items and build high-level categories for different sets of tasks, contexts, and robot appearances. The final set of high-level categories for task and context are home, office, and public (figure 3).

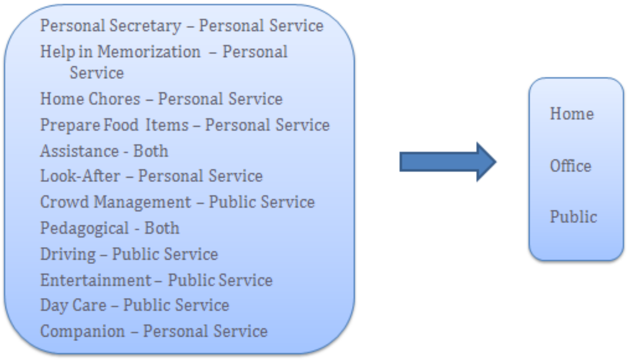



Figure 3: Graphical representation of exploratory study findings.

As for robot appearance, we divided the most common responses into two high level categories: (i) human-like or humanoid robots and (ii) machine-like robots (figure 4). Human assistants were later added as a control condition.

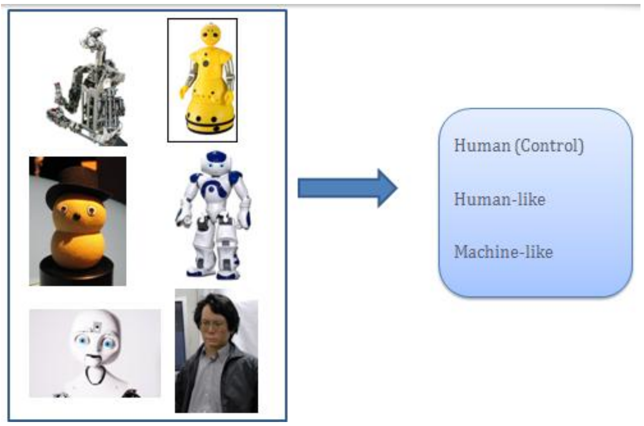



Figure 4: Graphical representation of exploratory study findings.

## 3.4 Discussion

Overall, these studies generated helpful results. These led us to identify different set of social goals and environments along with features of robots that are best matched with them. For example, one participant chose a personal robotic assistant for an office setting for a dictation task. He preferred that the robot not have a face, but a screen-mounted display for ease of use. Most participants gave detailed responses and preferred to customize their own robot drawings or descriptions for their chosen contexts and tasks rather than choose a robot from the given set of pictures.

Our analysis suggested that people prefer robots in places which are potentially dangerous for human beings e.g. traffic or public navigation especially around construction places. Additionally, when interaction with robots is part of a job or a daily compulsory interaction e.g. a personal assistant in an office environment, a robot that has some form of screen-mounted head is preferred over human-like robots. One reason for such a choice is their proximity in appearance to familiar on-screen graphical user interfaces. On the contrary, we found out that human-like robots are preferred for jobs or tasks that people like to get done in a home environment e.g. cooking or child-care. These findings were significant for our project as they lead us to form our hypothesis, as described in the following section.

***Limitations***—We only had access to a very targeted sample of the population (mostly undergraduate students with majors in computer or engineering). This may explain the limited number of contexts and/or tasks that were present in our analysis.

As mentioned earlier, we also provided a minimal description of each robot in each phase of our exploratory study. This proved to be problematic; we noticed that participants were trying to match the description of the robot with a task. So, instead of these descriptions being helpful, we felt that they restricted the creative thinking of our participants.

# 4. EXPERIMENTAL STUDY

## 4.1 Hypothesis

From the analysis of our exploratory survey findings, we formulated two hypotheses. The first hypothesis is related to the overall perceptions of different assistant types (including humans and robots) in any task and context. The second hypothesis is concerned with how certain assistant types may be perceived in a particular context.

**Hypothesis I**: *Humans should be perceived as best suited for socially interactive tasks, and human-like robots should be perceived as better suited for socially interactive tasks than machine-like robots* (figure 5).

**Hypothesis II:** *Humans should be perceived as best suited for all contexts, but human-like robots should be perceived as better suited for the home context and worse suited for the office and public contexts than machine-like robots.* (figure 6).

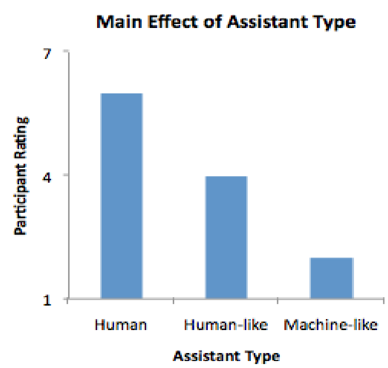



Figure 5: Graphical representation of hypothesis I.

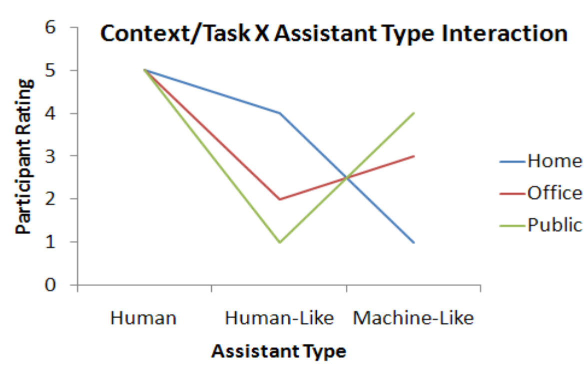



Figure 6: Graphical representation of hypothesis II.

## 4.2 *Methods*

Our experiment was a 3 (assistant type: human, human-like robot, machine-like robot) x 3 (context: home, office, public) within-subjects factorial design and between-subjects random levels in each of these factors. The human assistant type was used as a control group. The random factors were added to avoid bias of a particular assistant or a particular context type. Therefore, this factorial experiment had 36 treatment combinations (3x2 x 3x2) in total (figure 7).. Conditions were completely counterbalanced and randomized. Response variables consisted of 8 Likert-scale questionnaire items per image that measured efficiency, preference, goodness of fit, and comfort level of the assistant in a given task and context.

| Factor 1 (Assistant Type) | | Factor 2 (Context) | |
|---|---|---|---|
| **Human** | Male | **Office** | Dictation |
| | Female | | Mail Delivery |
| **Human-like robot** | Asimov | **Home** | Childcare |
| | Wakamaru | | Cooking |
| **Machine-like robot** | Papero | **Public** | Navigation |
| | An9-PR | | Education |

Figure 7: Factorial design

### *4.2.1 Participants*

Participants were 42 volunteers (22 men, 20 women) recruited from online forums and mailing lists. Ages ranged from 18 to 65 years (*M* =30.96, *SD* = 11.32).

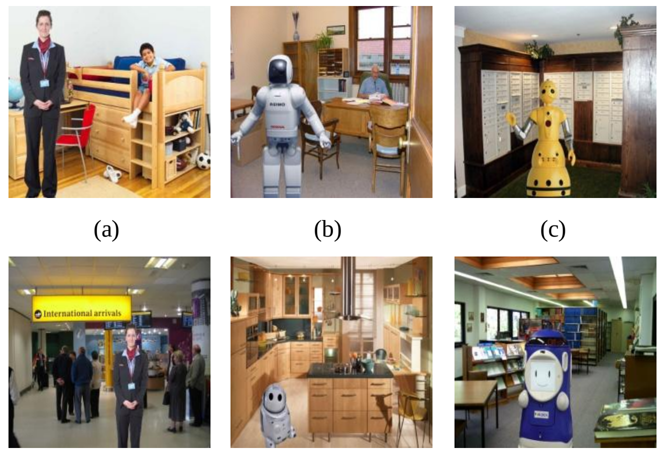
### *4.2.2 Procedure*

Subjects were each shown a randomized ordered set of nine images consisting of all combinations of assistant type and task context. For each of these 9 images, we provided a brief description of the assistant, context, and task. After viewing each image, participants answered eight Likert-scale questionnaire items.

| Response Variables | Question Statements. |
|---|---|
| Task efficiency | This assistant has the ability to perform this task efficiently |
| Context efficiency | It doesn't look like this assistant is able to function well in this environment. |
| Task preference | I would want this assistant to perform this task for me. |
| Context preference | I would like having this assistant in this context. |
| Task fit | I think this assistant is well-suited for this particular task |
| Context fit | I feel that this assistant is out of place in this location |
| Task comfort | I am comfortable with this assistant performing this task for me |
| Context comfort | Seeing this assistant in this location makes me feel uneasy |

Figure 9: List of response variables.

All of these items were measured on 7-point scales ranging from 1 (strongly disagree) to 7 (strongly agree). Subjects were also asked two additional questions for each image as a manipulation check i.e. to determine whether they correctly identified the assistant type, context, and task. Subjects were also provided additional text boxes for optional comments.




(a) (b) (c)

(d) (e) (f)

Figure 8: Sample assistant/task context images. (a) human assistant x home child care task context (b) humanoid robot x office dictation (c) humanoid robot x office mail delivery (d) human x public navigation (e) machine-like robot x home cooking (f) machine-like robot x public education

## *4.3 Results*

We applied a mixed model analysis of variance (ANOVA) on the data from all of our participants. The ANOVA found a main effect on assistant type for task efficiency ($F(2,379) = 80.46$, $p = 0.01$). Results demonstrated that human assistants ($M = 5.69$, $SD = 1.39$) were rated as more efficient for any given task and context than humanoid ($M = 4.27$, $SD = 2.10$) or machine-like robot assistants ($M = 3.59$, $SD = 2.20$) . The pairwise comparison between humanoid and machine-like robots was not significant. The ANOVA also found main effects on assistant type for task comfort ($F(2,379) = 447.12$, $p < 0.01$), task goodness of fit ($F(2,379) = 115.63$ $p < 0.01$), and task preference ($F(2,379) = 294.12$ $p < 0.01$). These findings illustrated that people were more comfortable with human assistants performing tasks for them ($M = 5.61$, $SD = 1.46$) than humanoid ($M = 3.91$, $SD = 2.15$) or machine-like robots ($M = 3.27$, $SD = 2.09$). The pairwise comparison between humanoid and machine-like robot assistants was also significant, which demonstrated that people were more comfortable with humanoid robots. Participants also rated human assistants as most fit for any task ($M = 5.34$, $SD = 1.56$) and humanoid robots as more fit ($M = 3.96$, $SD = 2.12$) than machine-like robot assistants ($M = 3.17$, $SD = 2.03$) for tasks. Finally, human assistants had the highest mean ratings ($M = 5.28$, $SD = 1.72$) for task preference, while humanoid robot assistants ($M = 3.80$, $SD = 2.21$) were preferred over machine-like assistants ($M = 3.13$, $SD = 2.12$) for tasks.

The ANOVA found no main effect on the task context factor for any response variables: task efficiency ($F(2,379) = 3.60$, $p > 0.05$), task comfort ($F(2,379) = 14.66$, $p > 0.05$), task goodness of fit ($F(2,379) = 7.73$, $p > 0.05$), task preference ($F(2,379) = 8.52$, $p$

> 0.05), context efficiency ($F(2,379) = 2.25$, $p > 0.05$), context comfort ($F(2,379) = 7.27$, $p > 0.05$), context goodness of fit ($F(2,379) = 3.79$, $p > 0.05$), or context preference ($F(2,379) = 6.40$, $p > 0.05$). The ANOVA also found no interaction between assistant type and task context for any response variables: task efficiency ($F(2,379) = 1.41$, $p > 0.05$), task comfort ($F(2,379) = 1.02$, $p > 0.05$), task goodness of fit ($F(2,379) = 1.11$, $p > 0.05$), task preference ($F(2,379) = 1.16$, $p > 0.05$), context efficiency ($F(2,379) = 2.31$, $p > 0.05$), context comfort ($F(2,379) = 1.32$, $p > 0.05$), context goodness of fit ($F(2,379) = 1.97$, $p > 0.05$), or context preference ($F(2,379) = 0.97$, $p > 0.05$).

The results of the ANOVA are summarized in the appendix (tables 1-4).

### *4.4 Discussion*

The results strongly supported hypothesis I: human assistants were preferred over humanoid and machine-like assistants in all context and task combinations and humanoid robot assistants were preferred to machine-like robots in all context and task combinations. This finding is consistent with the other related studies as mentioned in related work section of this report. However, no significant interaction was found between assistant type and task context. One alternative explanation for this finding is that context has little effect on people's perceptions of robot forms, since task is more important in determining expectations.. One limitation of this study was that we lacked a concrete distinction between a human-like robot and machine-like robot. As suggested in some of the comments left on our online experiment pages and the result of manipulation checks along with each image, few of our participants couldn't distinguish between a machine-like robot and a humanoid robot. 24 out of 42 participants provided a total of 75 comments, as visualized in the word cloud below (figure 10). Although the manipulation check suggested that participants correctly identified the intended assistant type, a more formal definition of human-like and machine-like robots is desired. Future research should explore the differences between and perceptions of human-like and machine-like robots as well as the implications their form and function may have on future paradigms of robot design towards socially interactive uses.


Figure 10: A word cloud of participant comments.

## 5. ACKNOWLEDGMENTS

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**Table 1:** The F values for our post-hoc and pair-wise comparison tests. Total number of observations for all tests was 381.

| Response | **Factor1: Robot Appearance** | | | **Factor2: Task & Context** | | | **Factor1 * Factor2** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **DF** | **F** | **P** | **DF** | **F** | **P** | **DF** | **F** | **P** |
| Task Efficiency | 2 | 80.46 | ** | 2 | 3.60 | **ns** | 4 | 1.41 | **ns** |
| Task Comfort | 2 | 447.12 | ** | 2 | 14.66 | **ns** | 4 | 1.02 | **ns** |
| Task Fit | 2 | 115.62 | ** | 2 | 7.73 | **ns** | 4 | 1.11 | **ns** |
| Task Preference | 2 | 294.11 | ** | 2 | 8.52 | **ns** | 4 | 1.16 | **ns** |
| Context Efficiency | 2 | 119.91 | ** | 2 | 2.25 | **ns** | 4 | 2.31 | **ns** |
| Context Comfort | 2 | 31.42 | * | 2 | 7.27 | **ns** | 4 | 1.32 | **ns** |
| Context Fit | 2 | 150.84 | ** | 2 | 3.79 | **ns** | 4 | 1.97 | **ns** |
| Context Preference | 2 | 3307.36 | * | 2 | 6.40 | **ns** | 4 | 0.97 | **ns** |

**Note:** P-values (ns=not significant, *p<0.05, **p<0.01, ***p<0.001) DF=degree of freedom.

**Table 2:** Comparison of human with both humanoid and machine-like robot. The response variables are given in the first column. Most of the results here are significant ($p < 0.05$) and also it shows that human are better suited, as measured by our response variables, for all tasks and contexts

| Response | N | M | SD | **Humanoid** | | | | **Machine** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | **N** | **M** | **SD** | **P** | **N** | **M** | **SD** | **P** |
| Task Efficiency | 127 | 5.69 | 1.39 | 127 | 4.27 | 2.10 | * | 127 | 3.59 | 2.20 | ** |
| Task Comfort | 127 | 5.61 | 1.46 | 127 | 3.91 | 2.15 | ** | 127 | 3.27 | 2.09 | ** |
| Task Fit | 127 | 5.34 | 1.56 | 127 | 3.96 | 2.12 | * | 127 | 3.17 | 2.03 | ** |
| Task Preference | 127 | 5.28 | 1.72 | 127 | 3.80 | 2.21 | ** | 127 | 3.13 | 2.02 | ** |
| Context Efficiency | 127 | 5.66 | 1.61 | 127 | 4.39 | 2.17 | * | 127 | 3.21 | 2.11 | ** |
| Context Comfort | 127 | 5.59 | 1.84 | 127 | 4.25 | 2.13 | * | 127 | 4.01 | 2.15 | * |
| Context Fit | 127 | 5.36 | 1.99 | 127 | 3.94 | 2.13 | ** | 127 | 3.39 | 2.16 | ** |
| Context Preference | 127 | 5.47 | 1.54 | 127 | 3.83 | 2.19 | ** | 127 | 3.18 | 2.12 | **ns** |

**Note:** P-values (ns=not significant, *p<0.05, **p<0.01, ***p<0.001) N=Participants, M=Mean, SD=Standard Deviation. The F-values for post-hoc comparisons are given in Table 1.

**Table 3:** Comparison of humanoid robots with machine-like robots. The response variables are given in the first column. The result shows that humanoids are better suited at given tasks and contexts then machine-like robots, as measured by our response variables. The post hoc test also shows that our results are significant ($p < 0.05$)

| Response | N | M | SD | **Machine** | | | |
|---|---|---|---|---|---|---|---|
| | | | | **N** | **M** | **SD** | **P** |
| Task Efficiency | 127 | 4.27 | 2.10 | 127 | 3.59 | 2.20 | **ns** |
| Task Comfort | 127 | 3.91 | 2.15 | 127 | 3.27 | 2.09 | * |
| Task Fit | 127 | 3.96 | 2.12 | 127 | 3.17 | 2.03 | * |
| Task Preference | 127 | 3.80 | 2.21 | 127 | 3.13 | 2.02 | * |
| Context Efficiency | 127 | 4.39 | 2.17 | 127 | 3.21 | 2.11 | * |
| Context Comfort | 127 | 4.25 | 2.13 | 127 | 4.01 | 2.15 | **ns** |
| Context Fit | 127 | 3.94 | 2.13 | 127 | 3.39 | 2.16 | * |
| Context Preference | 127 | 3.83 | 2.19 | 127 | 3.18 | 2.12 | ** |

**Note:** P-values (ns=not significant, *p<0.05, **p<0.01, ***p<0.001) N=Participants, M=Mean, SD=Standard Deviation. The F-values for post-hoc comparisons are given in Table 1.

**Table 4:** Summarizes the results of our pair-wise comparison tests between both of our main factors by expanding the individual levels. These comparisons are between assistant type (human (control), humanoid, machine-like robot) and context type (home, office, public).

| **Context** | **Response Variables** | **Human (H)** | | | | | **Humanoid (Hd)** | | | | | **Machine (M)** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **N** | **M** | **SD** | **P** | | **N** | **M** | **SD** | **P** | | **N** | **M** | **SD** | **P** | |
| | | | | | **Hd** | **M** | | | | **H** | **M** | | | | **H** | **Hd** |
| **Home** | Task Efficiency | 42 | 5.40 | 1.59 | *** | *** | 42 | 3.59 | 2.11 | *** | * | 43 | 2.83 | 2.14 | *** | * |
| | Task Comfort | 42 | 5.04 | 1.71 | *** | *** | 42 | 3.10 | 2.18 | *** | **ns** | 43 | 2.56 | 1.90 | *** | **ns** |
| | Task Fit | 42 | 4.83 | 1.75 | *** | *** | 42 | 3.21 | 2.08 | *** | * | 43 | 2.37 | 1.81 | *** | * |
| | Task Preference | 42 | 4.61 | 1.92 | *** | *** | 42 | 3.07 | 2.25 | *** | **ns** | 43 | 2.62 | 1.99 | *** | **ns** |
| | Context Efficiency | 42 | 5.50 | 1.64 | *** | *** | 42 | 3.83 | 2.22 | *** | ** | 43 | 2.69 | 2.05 | *** | ** |
| | Context Comfort | 42 | 4.95 | 1.96 | ** | ** | 42 | 3.90 | 2.34 | ** | **ns** | 43 | 3.49 | 2.18 | ** | **ns** |
| | Context Fit | 42 | 4.67 | 2.21 | ** | ******* | 42 | 3.40 | 2.16 | ** | **ns** | 43 | 3.26 | 2.30 | ** | **ns** |
| | Context Preference | 42 | 4.90 | 1.83 | *** | *** | 42 | 3.21 | 2.20 | *** | * | 43 | 2.47 | 1.76 | *** | * |
| **Office** | Task Efficiency | 42 | 5.70 | 1.33 | *** | *** | 43 | 4.62 | 2.03 | *** | ** | 42 | 3.54 | 2.27 | *** | ** |
| | Task Comfort | 42 | 5.64 | 1.32 | *** | *** | 43 | 4.41 | 2.02 | *** | *** | 42 | 3.30 | 2.12 | *** | *** |
| | Task Fit | 42 | 5.45 | 1.40 | *** | *** | 43 | 4.34 | 2.0 | *** | **ns** | 42 | 3.17 | 2.05 | *** | **ns** |
| | Task Preference | 42 | 5.45 | 1.53 | *** | *** | 43 | 4.27 | 2.06 | *** | *** | 42 | 2.95 | 2.02 | *** | *** |
| | Context Efficiency | 42 | 5.38 | 1.78 | * | *** | 43 | 4.76 | 2.17 | * | *** | 42 | 2.90 | 2.00 | *** | *** |
| | Context Comfort | 42 | 5.88 | 1.70 | ** | *** | 43 | 4.67 | 1.89 | ** | **ns** | 42 | 3.95 | 2.11 | ** | **ns** |
| | Context Fit | 42 | 5.55 | 1.78 | ** | *** | 43 | 4.34 | 1.93 | ** | *** | 42 | 2.92 | 200 | ** | *** |
| | Context Preference | 42 | 5.57 | 1.36 | *** | *** | 43 | 4.30 | 2.01 | *** | ** | 42 | 3.26 | 2.31 | *** | ** |
| **Public** | Task Efficiency | 43 | 5.98 | 1.18 | *** | *** | 42 | 4.57 | 2.03 | *** | **ns** | 42 | 4.36 | 1.96 | *** | **ns** |
| | Task Comfort | 43 | 6.11 | 1.12 | *** | *** | 42 | 4.19 | 2.05 | *** | **ns** | 42 | 3.95 | 2.03 | *** | ns |
| | Task Fit | 43 | 5.72 | 1.42 | *** | *** | 42 | 4.30 | 2.11 | *** | **ns** | 42 | 4.00 | 1.91 | *** | **ns** |
| | Task Preference | 43 | 5.76 | 1.51 | *** | *** | 42 | 4.04 | 2.17 | *** | **ns** | 42 | 3.81 | 1.89 | *** | **ns** |
| | Context Efficiency | 43 | 6.09 | 1.34 | *** | *** | 42 | 4.55 | 2.05 | *** | **ns** | 42 | 4.04 | 2.07 | *** | **ns** |
| | Context Comfort | 43 | 5.93 | 1.71 | *** | ** | 42 | 4.17 | 2.14 | *** | **ns** | 42 | 4.56 | 2.07 | *** | **ns** |
| | Context Fit | 43 | 5.86 | 1.78 | *** | *** | 42 | 4.07 | 2.21 | *** | **ns** | 42 | 4.0 | 2.08 | *** | **ns** |
| | Context Preference | 43 | 5.93 | 1.22 | *** | *** | 42 | 3.95 | 2.17 | *** | **ns** | 42 | 3.83 | 2.06 | *** | **ns** |

**Note:** P-values (ns=not significant, *p<0.05, **p<0.01, ***p<0.001) N=Participants, M=Mean, SD=Standard Deviation. Assistants: (H:Human, Hd:Humanoid, M:Machine). The F-values for post-comparisons are given in Table 1.