Improving Human-Robotic Interactions with Applied Human Factors Principles: Robot Factors and Solutions in Tool Design

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ABSTRACT

Robot Factors is an emerging term from research bridging theory and principles from Human Factors and human-robotic interactions. In today's world, new technologies and tools have been introduced into the workplace that transfers mundane and repetitive tasks away from humans to robots. However, current technological advancements do not enable human-robot interactions that meet human perspectives and social, interactive expectations. Thus the goal of this research is to apply human factors principles to robot factors so that robots are considered as end-users during collaborative tasks for optimal human-robot interaction. A survey was released to Tufts University Engineering undergraduate students, and Masters and Ph.D. candidates, where participants were asked to rank and scale design process steps, rank sorting process by feature, and levels of automation within each sorting process step for designing a tool to sort Legos into an NXT kit. Results showed priming had an influence on the ways in which participants ranked features in the sorting process of Legos, thus presorting physical feature of categories (i.e. shape) of Legos for human condition, while robot and team conditions defaulted to "mechanical" features (i.e. efficiency, task). Supported by the literature review and interpretation from the data, a list of recommendations was created to highlight how to improve human-robot interactions by introducing "Robot Factors".

Key Words: human-robot interaction, human factors, robot factors, perception, stereotypes, robotics, tool design.

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1. Introduction

Advances in technology have changed the ways humans complete various tasks and alleviate cognitive load from mundane tasks. For the better, technology has increased the amount of work humans can accomplish and minimizes the amount of cognitive load necessary to complete non-creative tasks. This enables humans to invest their higher cognitive processes in more creative, elaborate tasks, abstract thinking, and decision-making.

The introduction of new technologies and tools into the workplace has transferred mundane and repetitive tasks away from humans to robots. In some cases, successful task completion requires viewing robots as teammates rather than just tools. Collaboration can be particularly helpful when completing an over-arching task consisting of hierarchical subtasks.

Complimenting human factors, which is the practice of designing products, systems, and processes from the human user perspective, human-robot interactions can optimize the relationship, effectiveness, and efficiency for task and subtask utilization and completion. Currently many models and designs for human-robot interactions take the perspective of the human-user. However, increasingly robots are perceived as more than just a tool to humans.

As robot development improves, the utility of including a robot user or human-robot team in designing products, systems, and processes becomes more apparent. However, conceptualizing design specifically for a robot user or human-robot team is currently not fully taken into consideration. Furthermore, applying human factors principles for a robot end user has not been extensively researched or applied. Thus the goal of this research is to apply the process and principles of human factors to this newly found topic of ‘robot factors’ to ensure that when designing products and systems, robots are considered as end-users during a collaborative task(s) with a human(s) to ensure an optimal human-robot interaction.

From the earliest records of robots designed as mechanical knights by Leonardo da Vinci in the fifteenth century to social robots working in manufacturing companies, hospitals, nursing homes, robots are increasingly integral in our modern world. To engage as successfully as possible with humans, robots often take a mechanical human form, with humanistic physical and interactive features and affordances. Are their various levels and situations that affect the success of an interaction rather than the capabilities and limitations of the tool or teammate at hand? To optimize human-robot interactions, should designers take into consideration human-like characteristics or target design more specifically to the robot? Put another way, are designers over-attributing human characteristic on the abilities of robots when the technology has yet to catch up to this humanistic embodiment and interaction? Thus, entertaining the idea that having the focus on robots as their own end user may enable designers to truly understand the contextual limitations and strengths of robots.

Humans' strengths lie in higher cognitive processing, creativity, communication, and executive decision-making, while robots' strengths are in monotonous, repetitive tasks, storing and forgetting large amounts of data, and following explicit directions. Thus introducing "robot factors," the focus and emphasis on robots and their interactions, based on their design, purpose, and mechanical capabilities and limitations, with humans, equipment, and the environment. Applying this understanding to the dynamics and optimization of human-robot interactions will utilize each agent's strengths for successful task and subtask completion within a human-robot team.

1.1 HRI and Human Factors Meets Robot Factors

Human factors seeks to improve how people use and interact with their environments and products to optimize effectiveness, efficiency, and knowledge of task utilization, understanding, and completion (Wickens, et al., 2004). While human factors strives to understand human behavior and enhancing user experience, *robot factors* would aim to improve robots and human-robot teams effectiveness. Human factors focuses on the human as an end-user with a clear focus of how this specific end user is interacting with their environments and products, robot factors shifts similar human factors principles and approach to robots as end users. From human factors principles, a designer can apply and gauge understanding from mechanical capabilities and limitations of a robot, and how this end user is interacting with its environment and product specifically designed for it to optimize effective and efficient task utilization and completion—focusing on these specific principles may improve current human-robot interactions.

Existing research lends a hand in establishing the current framework of how designers and engineers conceptualize robots in human-robot interactions and provides a starting point to this research. Kanda and Ishiguro (2013) completed three studies exploring and introducing modeling natural behavior into human-robot interactions. The first study focused on deictic interactions, which refers to words (like *this* or *that*) that take on meaning within a context of use from spoken references and gestures. Humans often use deictic interactions when describing things they are bringing attention to through speech or gesture as points of references. Therefore supporting the notion that people could gather new information more easily from a robot when deictic interactions were to be used (Kanda & Ishiguro, 2013). While the second study focused on the proxemics phenomenon people use during conversations. During conversation, people adjust their distance based on the situation and relationship to the others they are interacting with (Kanda & Ishiguro, 2013).

The final study focused on integrating nonverbal behavior for direction-giving scenario (Kanda & Ishiguro, 2013). Though robots can be mobile, recent studies continue to support people's concerns about appropriate distances between a human and a robot. Incorporating natural gestures during direction giving from a robot to a human would increase the chance of a more positive interaction. While each study focused on a different characteristic people use when interacting with others, utilizing these natural interactive behaviors suggests a successful human-robot interaction and may in fact benefit the collaboration of a human-robot team (Kanda & Ishiguro, 2013). Yet, some of these conclusions stem from a supervisor/subordinate assignment role, rather than a collaborative approach where each agent's strengths are combined in achieving a common goal.

Introducing natural interactive behaviors leads to more successful human-robot interactions, specifically when people are giving directions to robots (Kanda & Ishiguro, 2013). For instance, when talking to a robot, humans pick up on nonverbal cues in an attempt to understand a robot's internal state (Kanda & Ishiguro, 2013). Before noting the physical design of the robot, humans automatically pick up on these nonverbal cues, making this an important factor in human-robot interactions (Kanda & Ishiguro, 2013). Additionally, findings in social robotic studies imply that gender and personality are also factors influencing the interaction between humans and social robots. What fosters user acceptance lies within the gender and personality of a social robot that *correctly* corresponds to our mental models in stereotypical roles (Tay, Jung, & Park, 2014).

Proximity is an important factor to consider when understanding human-robot interactions and modeling a positive interactive experience. Investigating social distance provides a lens in which to better understand and improve human-robot interactions and create guidelines for improved robot design. When observing through a supervisory/subordinate role assignment, a more positive experience occurs when cooperatively interacting with a robot that is distant (Kim & Mutlu, 2014). In fostering cooperation with a robot, consistency within a robot's status and proxemics are important (Kim & Mutlu, 2014). Understanding the implications of current human-robot interaction processes and systems, human factors principles applied to robot factors, and to the stereotypes, perception, and expectations of robots, we can gauge a deeper analysis of how people conceptualize the agent for whom/what a tool is being designed.

1.2 Stereotypes and Perceptions Influencing HRI

While humans' strengths lie in perception and higher cognitive processing, it's argued that robots could benefit from the collaboration and directions of human users, while being considered as active team members or partners (Fong, Thorpe, & Baur, 2003). Robots are notorious for their strength in algorithmic processing and precision, storage and deletion of memory, and mechanical capabilities of completing redundant tasks. However, mental models, stereotypes and perceptions of robots may inhibit robot-human team performance. Referring to people's conceptual framework, mental models assist people in their predictions and orientation of the world (Kiesler & Geotz, 2002). This limits perceptions of a robot's capabilities into a finite range when viewed solely as tools performing on task commands, rather than automatically as teammates or partners (Fong, Thorpe, & Baur, 2003).

Delving into the robot's design and purpose, applying our mental models can assist or limit the ways we conceptualize a robot as a tool or teammate. Factors such as the robot's physical and spatial design and/or whether working on a task either simultaneously or separated through time and/or spatial location, may affect human-robot interactions. Interests in developing socially interactive robots that accurately mimic human characteristics are in demand (Tay, Jung, & Park, 2014). However, humans have many stereotypes and perceptions of a robots capabilities and flaws, and if a robot's characteristics are too similar to humans, then this alters realistic expectations (Mori, Macdorman, & Kageki, 2012). Therefore, creating this unrealistic expectation may increase the likelihood of a negative user experience and hinder and/or elongate successfully completing a task, as technological advancements have yet to cater to this unrealistic expectation.

Robots have difficulties with perceptual functions such as object recognition and assessing situations, while also having difficulties with unstructured decision-making (unpredicted or unprepared situation(s) that may arise). Robot-human teams would benefit from extracting and combining the strengths of both agents, respectively. However, this requires understanding these separate strengths. Collaborating on tasks to achieve a common goal increase task completion success, rather than limiting the interaction due to the robots flaws and/or confining the interaction to a supervisor/subordinate assigned roles. This collaborative approach varies from current expectations and perceptions of robotic behaviors from our mental model, and encourages and demands human-like interactive behavior.

Humans project social constructs (such as gender, stereotypes, and personalities) onto social robots they interact with. This creates complexities within human-robot interactions. Thus increasing the likelihood of a negative user experience to the ways in which humans perceive and accept social robots. Suggestions from social heuristics (heuristics refer to mental shortcuts), designers should lay a foundation in grouping specific characteristics that encompass social role stereotypes and apply this to future designs, because humans use stereotypes as shortcuts and prefer social robots with matching occupational personality and gender (Tay, Jung, & Park, 2014). However, does this reinforce narrow methods in interacting with social robots and distract from the task at hand to complete? This may hinder the interaction when introducing other environmental factors to a task, where collaboration is necessary and stereotypical role is insignificant. Thus, if designers perpetuate stereotypical roles based in narrow-minded social constructs, it may overall be detrimental within a human-robot interaction.

1.3 Automation and social robots

For human-robot teams, many design issues stem from a sole focus on technical features automation can provide. However, in human factors research, human-centered automation focuses on the addition of human performance to what automation can provide a human operator or supervisor, thus the human-robot team (Wickens, Hollands, Banbury, & Parasuraman, 2013). This research focuses on designing effective tools for a specific end-user, comparing between a human user alone, a robot user alone, and a human-robot team.

Various levels of autonomy within the human-robot team influence the overall performance; and when interdependence is ignored, increased autonomy leads to the degradation of performance (Johnson et al., 2012). Thus supporting the notion of collaboration where there is equal participation in shared subtasks. Based on assessments of current human-robot team designs, burden and opacity of the task were assessed. In assessing burden, the increase of autonomy decreased the amount of burden a human operator would experience. Then while assessing opacity, which refers to the human's situational awareness, increasing autonomy increases the human operators understanding of the situation and can anticipate the robot's behavior. Therefore, concluding the more autonomy given to the robot, the less the human understood what was going on (Johnson et al., 2012). Thus, equal collaboration is necessary to ensure situational awareness to execute decisions and enhance teamwork.

The leveling of trust in an autonomous system stems from conditions based on the human operator's task load and introduces autonomous bias. Autonomous bias refers to aids to humans in decision-making within a complex environment (Wickens, Hollands, Banbury, & Parasuraman, 2013). However, if the human operator understands less of what is happening, this may lead to distrust of the autonomous system the human operator is working with.

This leads to the belief that transparency and control may be more important to a human operator than level of autonomy based on the characteristics of the task at hand when designing for effective human-robot teams. Research shows the correlation between trust and automation concludes the more a human trusts an agent (human or machine), creates dependency on said agent. Trust is a subjective, cognitive assessment used during interactions with autonomous systems (Wickens, Hollands, Banbury, & Parasuraman, 2013). However as examined within automation, increased levels of autonomy leads to degradation in performance and interdependence among team members (Johnson et al., 2012).

As outline in *Engineering Psychology and Human Performance*, the authors divide design tactics based on feedback, appropriate levels of automation, human-automation etiquette, and display design and training to improve performance for human-robot teams. Human-automation etiquette is applied in this research. These authors present the argument that designers should make an effort to display information of the autonomous system based on critical information regarding current status and the status of the process being monitored or controlled (Wickens, Hollands, Banbury, & Parasuraman, 2013). Similarly supported, Johnson et al. (2012) discusses in their method of Coactive Design robots can be envisioned as teammates through interface design, algorithmic controls, and human-like behavior.

This purposed Coactive Design is based on observability, predictability, and directability (OPD) for human-robot interfaces: observability is the ability to observe and interpret pertinent signals; predictability should be predictable enough for others to reasonably rely when considering actions; and finally, the ability to direct the behavior of others and complementarity directed by others (Johnson et al., 2012). Emphasis on best utilizing OPD enables designers with key guidelines for system requirements and detailed specifications for human-robot teams.

OPD includes the human performance perspective enabling a human user as the supervisor of a task and to better work together with a robot-agent to complete a task based on interdependence in completion of a task for a human-robot team. Designers must be aware of the level of automation as higher degrees of automation with decrease workload and/or increase routine performance. However, increasing automation may in turn increase "out of loop unfamiliarity", which then affects degrade failure management (Wickens, Hollands, Banbury, & Parasuraman, 2013).

System performance metrics give value to understanding how task completion is being optimized. System performance as a common metric assesses how well the human agent and robot perform as a team can be measured quantitatively, subjectively, and mixed-initiatively (Steinfeld et al., 2006). Quantitative measure can include the effectiveness and efficiency a task is being displayed by percentage of the task completed and time required for the task, respectively. On the other hand, subjective ratings can be utilized as a metric for assessing quality. Lastly, mixed-initiatives for a human-robot team lies in the ability to regulate who has control during specified times within completing the task (Steinfeld et al., 2006).

In conclusion, when assessing specific metrics of "how well" a human-robot team is completing a task, metrics assessing for both the human and robot are situational awareness, workload, and autonomy. Appropriate levels of each enable each independent agent to assist the other in completing the task optimizing efficiency and effectiveness. These metrics may be displayed such that the human operator may view, assess, and pivot when necessary to ensure optimization of task completion. Human operators can be trained accordingly in understanding meaning and assessing these displayed metrics. Furthermore, pivoting when necessary due to interaction aspects that hinder completing the task effectively and efficiently.

1.4 Meet The Baxter

Currently the notion to include human-like characteristics into robotic design increases the likelihood of humans to positively interact with robots. However, are we too focused on human-like characteristics and not further expanding into robotic characteristics to successful complete a task? In this experiment, The Baxter by Rethink Robotics, which is an interactive production robot, played the roll as the robot prime. Due to its proven solutions for task completion, The Baxter is the perfect robot agent to utilize during this experiment. Though the initial description at first glance markets The Baxter well, reading between the lines reminds the audience that the Baxter was created solely to alleviate humans from monotonous tasks, and for a superior/subordinate role assignment rather than equal collaboration.

By its design, it's safe to be around and acting as Baxter's head, a screen features digital eyes and eyebrows that through a 360 degree sonar and front-facing camera, the eyes "can follow" what it's *looking* at, and can recognize people, parts, and it's environment. Baxter also features cameras on its limbs for "vision-guided movement and object detection for precision and versatility" (Baxter, 2015). Baxter is trained not programmed to complete its task--with behavior-based intelligence. Meaning, it has the capabilities of being manually trained by it's surrounding workers and can retain this training. All in all, Baxter contains humanistic characteristics; however, still does not perform to the caliber of a human's performance and approachability due to its design.

1.5 Lego NXT

As part of the experiment, the Lego NXT kit is used in setting the scene for our participants and the Baxter in the tool design process task. Legos was created in Denmark in 1932. However, since it's inception, Lego has created Mindstorms Education has been marked as the next generation in educational robotics, which enables students to discover STEM in a fun and engaging way.

1.6 Experimental Goals

This study explores different prioritization and conceptualization of tool use for different end-users: human, robot, and human-robot team. The Baxter is used as the robot agent, while the Lego NXT kit the storing task at hand for the participant. We aim to research the ways in which participants describe their agent for whom/what they are designing, the *appropriate* process, and better understanding how an individual's mental model of robots biases their thought process for design.

Currently, there is not much research how altering the conceptualization in tool design in regards to robots and human-robot teams as end users. Our interests' lie in how participants' thought and design process of simple tools for a human user, robot user, or human-robot team influenced participants' design choices. Thus aiding our understanding of the relationship between the intended user of the tool and design principles based on the participants responses.

2. Methods

Robots and artificial intelligence has been studied for decades; however, research in understanding the implications of robot factors within human-robot interactions has yet been completed. We began by collecting information through a survey to understand the thought and design process of Tufts engineering students of a simple tool to complete mundane tasks. The following research was approved by Tufts SBER IRB (protocol: 1412001).

2.1. Research Survey

The research survey focused on the design process of tools aiding completion of mundane, automatic tasks that lasted no longer than 30 minutes of a participant's time and consisted of 11 questions. We solicited Tufts engineering students to complete one of the three conditions in the survey. There were a total of 147 participants were solicited. Of the 147, only 61 participant's data was available for use as many either just clicked the link and then exited out or actually began the survey, but didn't complete it.

To participate in this study, participants needed to consent they 18 years or older, and confirm they were an engineering student (although engineering psychology or computer science from either the engineering or arts and sciences school were also included) and. The survey was divided into three main sections to understand how participants would begin to think about how to create a tool to sort Legos, what sorting process would be needed to sort a Lego NXT kit, and scale levels of automation that would be considered ideal for each step of a sorting process.

Participants were randomly assigned one of three primes in the form of thirty-second video clips: 19 were given the 'human' prime, 23 were given the 'robot' prime, and 19 were given the 'team' prime. Once exposed to one of the three conditions, participants ranked by what order should a Lego NXT kit be sorted based on size, shape, color, or other; with a follow up question on qualitatively gathering their thoughts on why they chose the order that they did. Next, we asked participants what is the most important characteristic to sorting Lego bricks based on speed, accuracy, or ease.

Participants were then asked to think about tools they would design to sort and unorganized Lego NXT kit and rank the level of automation per specified set in the sorting process. Participants ranked from Level 1 to Level 7:

- Level 1: Manual control
- Level 2: A machine offers suggestions
- Level 3: A machine offers a specific option(s)
- Level 4: A machine suggests a specific action and offers to execute the action
- Level 5: A machine suggests a specific action and gives agent time to override it
- Level 6: A machine executes action then informs agent if asked
- Level 7: Full automation--machine completes the task and ignores the agent

Participants ranked eight specific steps that are found in sorting. Following this ranking, participants were asked about the factors they considered when selecting specific levels of automation for each step. Finally, participants answered demographic questions on their program, year of graduation, focus of study, age, gender, and race/ethnicity.

3. Results

All statistical analyses involved simple correlation, Chi Square Test of Association, and Kruskal-Wallis H Test with prime as the independent variable and ranking factors in the 'design process', sorting process ranking factors, and levels of automation scaling factors as dependent variables. All dependent variables were categorically recoded and collapsed to enable thorough inferences and understanding from the data's outcome.

When analyzing the data, the three main categorical variables of interest were recoded and collapsed. This was done to see if participants were answering similarly throughout the open-end response questions to conduct quantitative data analyses. The major themes within each categorical variable were recoded, and from there each recode was collapsed into similar categories. Ranking factors in the 'design process' initially had seven categories: Design Process, Efficiency, Research, Organization, End Product, Problem Solving, and End User. The sorting process factors initially had eight categories: Efficiency – Shape, Presort Categorization –

Feature, Efficiency – Size, Efficiency – Color, Presort Categorization – Feature Relevance, Presort Categorization – Ease, Efficiency, and Vision – Shape. Finally, the levels of automation scaling initially had 11 categories: User Ease, Experience, Time, Task, Human input and execution, minimize error, Machine execution and human assistance, No human input, Robot execution and no human input, Human execution with robot automation, Robot ease and human assistance, and Robot ease and time. All categories within each variable were collapsed for more concise groupings for data analysis.

Ranking factors in the 'design process' categories were collapsed into four categories. From the participants word choice and detail to the open-ended question referring to factors that influenced their ranking these are the categories created for this variable: design process, end product & user, scientific approach (research), and efficiency. The sorting process categories were collapsed into two categories: Efficiency – "Feature" (i.e. function, time) and Physical Feature (i.e. shape, size, color). Finally, the levels of automation scaling categories were collapsed into four categories: spotlight on human involvement (focus was on a human's execution or authority), spotlight on non-human involvement (participants here stated either robot or machine, though the focus was on this agent rather than a human agent), user-ease (end user ease, with these exact words used), and external factor (i.e. time).

3.1 Participant Demographic Information

Participants were students in the Engineering School at Tufts University, with the exception of students in Arts and Sciences majoring in Engineering Psychology and Computer Science. Of the participants, 48 responded with what program they were a student in: there were 31 undergraduate students, 12 Masters students, and five Ph.D. students (Figure 1). Only 48 participants reported their gender. There were 16 females and 32 males (Figure 2). Only 47 participants reported their race/ethnicity, where there were 36 identifying as White, seven identifying as Asian, three identifying as 'Other', and one identifying as Black/African American. Only 46 students reported their age, $M = 22.2$ years, $SD = 3.22$.

3.2 Correlations and Chi Square Tests for Association

Simple correlations and Chi Square Tests for Association were completed to see if the primes influenced specified categorical variables: ranking factor for the 'design process', sorting process ranking, and/or levels of automation scaling factors. Key findings and applicability to current research's hypothesis were found within the sorting process ranking factors and the levels of automation scaling factors.

First, prime and ranking factor for 'design process' was conducted. The two variables showed no correlation, $r(45) = -.175$, $p > .05$. Thus showing there was no effect of the prime on the ways in which a participant ranked any step of the 'design process'. Next, prime and sorting process ranking correlation was conducted. The two variables showed a significant correlation, thus showing based on the prime a participant was exposed to affected the manner in which they labeled the sorting process, $r(45) = -.370$, $p < .05$. Thus showing that when a participant was primed with the human condition, they were more likely to rank the sorting process based on physical features of a Lego piece, rather than external factors (i.e. function or time) or specified optimal manner (i.e. efficient process).

Finally a simple correlation between prime and levels of automation scaling factors was conducted. These two variables also showed significant correlation, thus displaying the ways in which a participant scaled specific steps in the sorting process by influenced by which prime they were exposed to, $r(45) = .399$, $p < .05$. Thus showing if a participant was primed with the human condition, they were more likely to highlight the role of a non-human in the automative process to ensure the human's needs were met during the sorting process. Furthermore, if a participant was primed with the robot condition, they were more likely to highlight the role of a human in the automative process of sorting to ensure the task was completed correctly, rather than other factors such efficient timing or collaboration.

Following the simple correlation, Chi Square Test for Association was conducted on all three categorical variables and the prime. This was conducted to see whether or not participants responded in a particular fashion due to the prime to which they were exposed. Through this test, most of the interest lies in Pearson's Chi Square value to note whether or not responses differed based on how participants were primed.

While analyzing prime and the ranking factors for the 'design process', this test showed no statistical significance between these two variables, showing the prime had no influence on the way in which participants ranked each step within the 'design process', $\chi(8) = 5.258$, $p > .005$ (Figure 3). There was a similar frequency distribution of each category within each prime, thus an interpretation can be made that there was a weak association between the prime conditions showing that participants ranked each step in the 'design process' similarly regardless of the prime.

Following this analysis, a Chi Square test showed statistical significance between prime and the sorting process, showing that in fact the prime influenced the way participants categorized the sorting, $\chi(2) = 9.277$, $p = .010$ process (Figure 4). As shown in Figure 4, when primed with the human video clip, participants tended to sort pieces based on category based on shape, size, etc. While when primed with either the robot or team prime, participants tended to sorting pieces based on which process or method is efficient.

Finally, the Chi Square test between prime and the levels of automation scaling showed statistically significance, thus showing the prime influenced the way in which they scaled the level of automation in various steps encompassing the sorting process, $\chi(6) = 19.571$, $p = .003$ (Figure 5).

3.3 Kruskal-Wallis H Test

A Nonparametric test was conducted on one of the variables of interest due to the small sample size and high participant dropout rate. A Kruskal-Wallis Test (also known as an H Test) was conducted on the levels of automation scaling factors.

Because the H Test does not assume the data is normally distributed between all three primes and the levels of automation scaling, this is a key advantage to analyzing sparse data due to high participant dropout rate.

The analysis showed that there was no statistical significance in the prime for each scaled level of automation of the sorting process step. Thus displaying no differentiating element of how sorting process items were scaled based on each prime (please note this table or refer to Figure 6):

Sorting Step	Chi Square	df	Asymp. Sig.
Analyzing all the Legos	0.130	2	0.937
Organizing Legos	0.806	2	0.668
Sorting Legos into subgroups based on color	2.269	2	0.322
Sorting Legos from subgroups into smaller groups based on size	1.421	2	0.491
Placing small Lego pieces into kit	2.434	2	0.296
Placing large Lego pieces into kit	1.787	2	0.409
Rechecking to see all Lego pieces are in the correct place with correct amounts	0.878	2	0.645
Putting the kit away in storage	0.753	2	0.686

Table 1: The statistical metrics of the Kruskal Wallis (H) Test for prime and levels of automation in sorting steps.

4. Discussion

4.1 Summary and interpretation of Results

This survey aimed to investigate the design principles of humanistic design versus robotic design and its implications on human-robot interaction. Using the ranking factors for the 'design process', sorting process ranking factors, and levels of automation scale, the goal was to quantify the designer's approach to humanistic versus robotic design. Finally, it was to investigate how the design process is influenced by a specific end user, either a human, robot, or team condition.

4.2 Implications for Applied Human Factors Principles in Robot Factors

Humans operate on different principles when completing a task that designers or engineers are attuned to. Introducing robots into the equation still focuses the human as the lead end user—which may introduce issues with overall user experience and optimization of task utilization and completion in the scope of a collaborative environment. Thus encouraging designers and engineers to consider the robot as an end user for a tool. Regardless of whether or not there is a difference between prime and ranking factors for 'design process' steps, there are two main conclusions that can be formalized: 1) currently, due to the number of participants, the data might be insufficient to warrant a conclusion or 2) there truly is no prime influence on how participants ranked a particular step in the 'design process'. Currently, when humans are interacting with robots in a supervisor/subordinate assignment role, introducing natural interactive behaviors leads to more successful human-robot interactions (Kanda & Ishiguro, 2013). However, since the technology available today has yet to fully incorporate these human user needs, human-robot interactions have an increased likelihood of decreased human user experience and effective and efficient task utilization, understanding, and completion.

4.3 Implications from Sorting Process

Comparing the human condition with the robot and team conditions shows a difference in how participants ranked the sorting process of the Lego pieces. Both the robot and team conditions showed similar distributions, thus supporting the assumption that due to a robot's limited capabilities, it "forces" a human user to conform to the robot's limited scoop to effectively and efficiently complete a task. However, this assumption from the participants may not be the path that ensures an increased likelihood in a successful human-robot interaction and optimal task completion.

Within the human condition, participants focused on humanistic strengths such as sorting through visual features or experience. Whereas the focus within the robot or team conditions focused on an "efficient" manner in completing a task—again the interpretation of this is that participants are focusing on the robot's limitations rather than its strengths it could contribute to enhancing the interaction and optimizing task completion. This supports the argument humans' mental models focus on the robots capabilities in a finite range to being solely a tool rather than a teammate or collaborative partner (Fong, Thorpe, & Baur, 2003). Thus when ranking in order of importance what features to focus on during the sorting process, the majority of the participants in the human condition focused on humanistic strengths. These strengths for sorting are used by humans when completing a task, like sorting Legos, thus focusing on presorting categories such as shape, size, color relevance between the Legos pieces that can easily discriminated, as human visual perception analyzes shape before color (Wheeler, 2012).

Furthermore, participants who were primed with either the robot or team condition reported factors with more "mechanical" features to sort the Legos. Thus focusing on a sorting process where a level of efficiency and a feature (i.e. shape) were the outcome. Another conclusion to this finding can also uncover how participants were conceptualizing the robot or the team, respectively based on their randomly assigned prime. Since humans' conceptualization on robots is on their finite capabilities, while also viewing them as a tool (Fong, Thorpe, & Baur, 2003), even when participants were primed with a team condition, they still reported similar themes found in the robot condition. Regardless of priming participants to consider both the human and robot users in collaboration, they still reported factors of sorting the Legos similar to participants with the robot prime. Therefore, this may mean that participants when primed with some level of a robot is seen as the leading agent to determine what factors were considered for the sorting process.

4.4 Implications from Levels of Automation

Next focusing on the prime and the levels of automation scaling, the prime had no influence the way in which participants scaled levels of automation during a sorting process as shown from the Kruskal-Wallis H test. A few questions were raised from this finding: do participants in fact truly understand what automation is? Is there truly no difference between prime groups? If true, the end user has no effect on how automated participants wanted a system to be. This is important to keep in mind, as

From the frequency distribution, participants who were in the human condition had an emphasis on a human end user executing and or evaluation evaluating portions, if not all, of the sorting process. While in the robot condition, the emphasis was on a robot or machine agent to execute the majority, if not all, of the steps to sorting. However, there were instances where participants stated they wanted to ensure the entire sorting process was done correct, thus a human end-user would intervene and evaluate the process, which offers a slightly different conclusion to what automation's main purpose (Wickens, Hollands, Banbury, & Parasuraman, 2013).

Participants primed with the team condition were most prone to reporting the end user as the main factor for ranking the sorting process steps. Interestingly, a couple conclusions can be made from this reporting: either 1) participants were unsure as to who the end user was and wanted to ensure automation complimented the end user or 2) wanted to the highlight a specific end user. However if this is the case, as seen in themes within the literature review and the results, if the focus is on a robot end user in a non-collaborative framework, the human-robot interaction will be negatively impacted—user experience and optimal efficiency and effective task utilization, understanding, and completion may decrease (Steinfeld et al., 2006). Furthermore, due to findings from this research, the end user has no effect on how automated a system should be.

5. Conclusion

Understanding the factors that shape how people approach a design process (and specifically in this case a tool) and conceptualize robots gives insight in improving human-robot interactions. Applying the process and principles of human factors to this newly found topic of 'robot factors' with the above recommendations ensures that when designing products and systems, robots are considered as end-users during a collaborative task(s) to improve and optimize the human-robot interaction.

5.1 Limitations

The results presented in this study had a number of limitations. First, only soliciting to students who were engineers here at Tufts University (regardless of program, i.e. Undergraduate, Masters, Ph. D) limited the scope to having the ability to generalize these finds to all designers and engineers. For example, Tufts University's engineering programs rigorously highlights design processes throughout various curriculum concentrations (based on what specific concentration and program a student is enrolled). Furthermore, this could have affected the ways in which students ranked the various steps in the 'design process' list presented to them solely due to exposure to their respective design process in their concentration's curriculum.

Second, due to the lengthy online survey, there was a high attrition rate among participants. Out of the 147 participants who engaged with the survey, only 61 participants' data could be used. Although this also presented its own challenges within this usable data, there was still missing information in, i.e. skipping over questions to shorten the time completing the survey. Finally, these limitations did present a challenge when analyzing the data; however, an analysis of understanding how participants were thinking about the design process and the end user and/or method at hand compliments the experimental lab study being conducted after this research. Further research is necessary to better understanding how primes are effecting the ways in which engineers and designers are 1) conceptualizing who or what the appropriate end user is, and 2) applying this understanding with human factors principles to robot factors to ensure optimal human-robot interaction for efficiency, effectiveness, and overall positive user experience when completing tasks.

5.2 Future Research

Through collaborative efforts with Aleksandra Kaszowska, a Masters and Ph.D. candidate for Cognitive Psychology at Tufts University, this survey's original framework was established as exploratory research for an experimental lab study to be conducted during the late spring of 2015, and throughout the summer at Tufts University. Kaszowska's study aims to investigate how tool design principles employed by engineers change as a function of the intended end user, similar to this research. However, in Kaszowska's study, participants will be asked to think aloud (a method where the participants are asked to narrate their thought process out loud as they are completing a task) with simultaneous eye tracking (using eye-tracking glasses). This will investigate how cognitive load, dwell time over particular areas of interest, and other parameters change in relation to factors such as experience of designer and intended user of the tool.

5.3. Robot Factors Recommendations

Current solutions can focus on creating a framework where humans and robots are labeled as collaborators. With this framework established, understanding the capabilities and limitations of each end user will increase the likelihood of a successful interaction and task completion. Recommendations for improved human-robot interaction are as follows:

- Applying human factors principles to robot factors by focusing the needs, limitations, and capabilities of a robot as an end user and the way in which it's intended to interact with its environment and products.
- Frame an interaction with a robot user as a collaborative task to increase the likelihood of a more positive user experience and optimal task utilization, understanding, and completion.
- Train human users on the limitations and capabilities of their collaborating robot user to establish realistic expectations for the interaction
- When creating the collaborative environment, ensure that both the human user and robot user's strengths not only are highlight, but compliment each user for the over success of task completion.

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APPENDIX

A. Figures

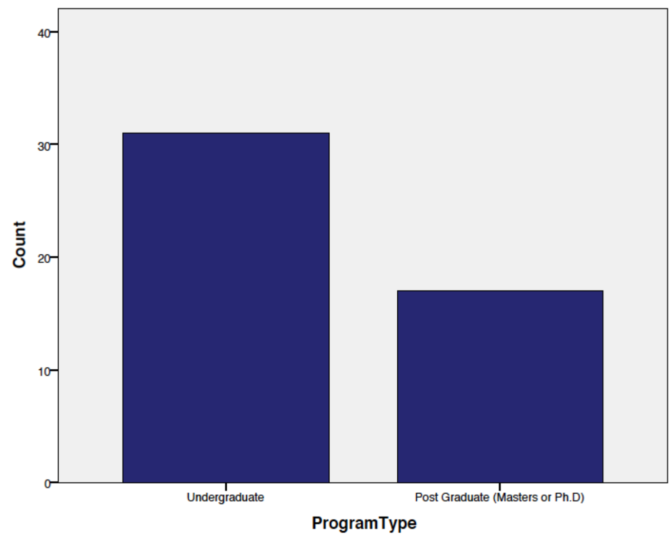

Figure 1: Participants reported they were either currently undergraduates or in a post graduate program (Masters or Ph. D. candidates). This gives a visual representation of the amount of engineering experience was present during the collection of data.

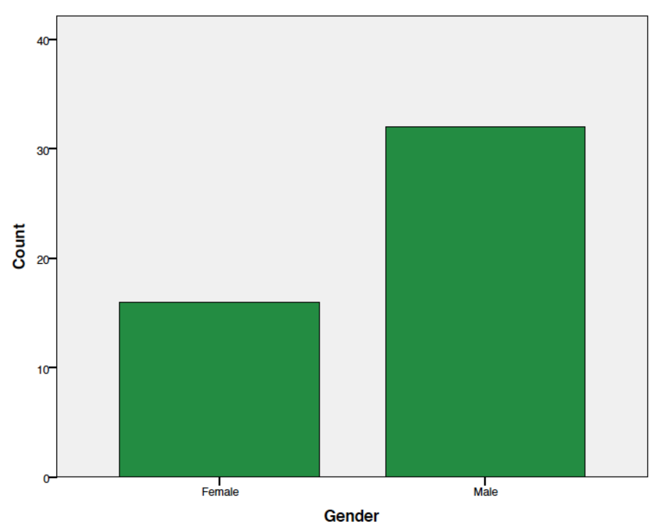

Figure 2: All participants reported their gender as either female or male. This gives a visual representation of the frequency of each self-identified gender.

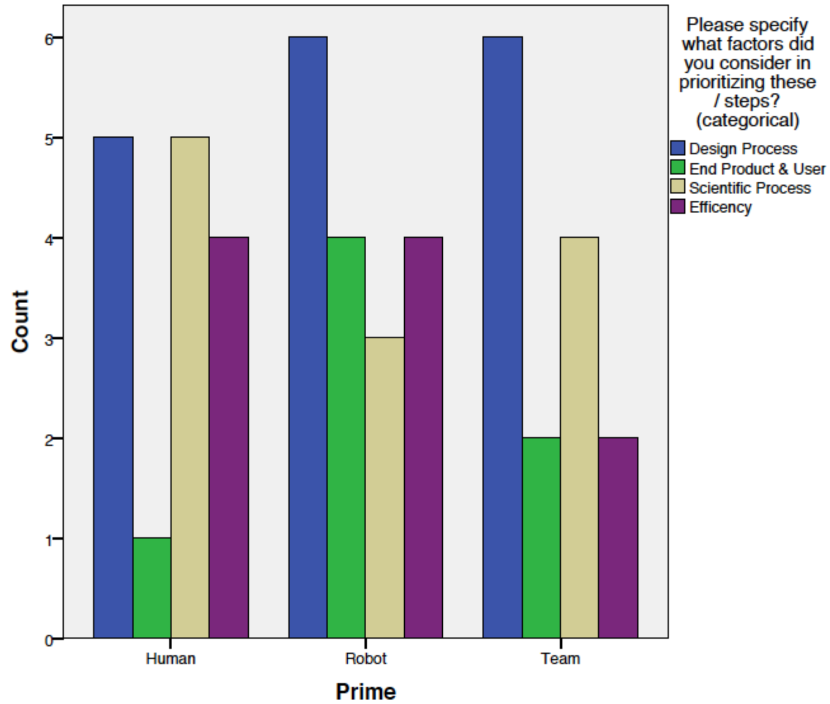

Figure 3: Results from a Chi Square Test for Association shows here no statistical significance between prime and ranking factors in the 'design process'.

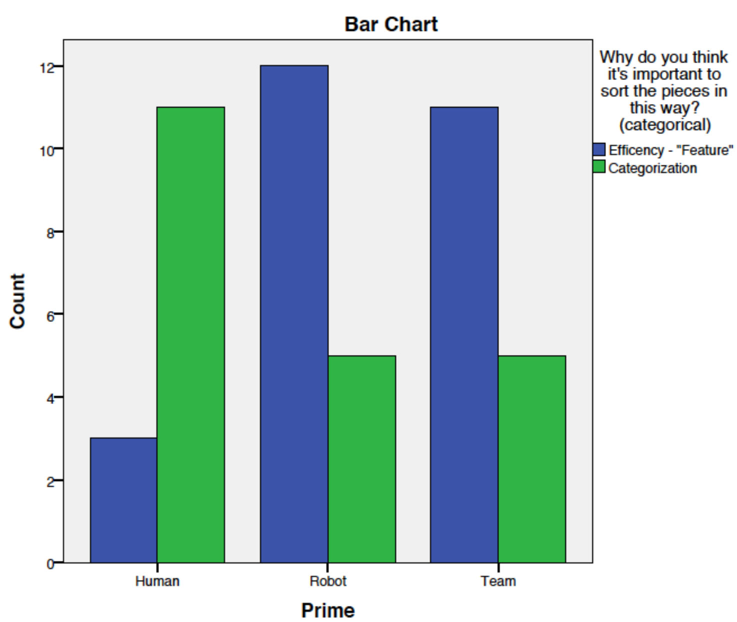

Figure 4: Results from a Chi Square Test for Association shows statistical significance between prime and sorting process rankings. Based on interpretation from this graph, it can be argued that humans are perceived to

sort based on humanistic strengths for sorting, while entities including robots are perceived to sort based on efficiency. It can also be noted that the entities including a robot seemed to have the robot as the lead 'user' for the sorting process—focusing on a sorting process appropriate for an entity that includes a robot.

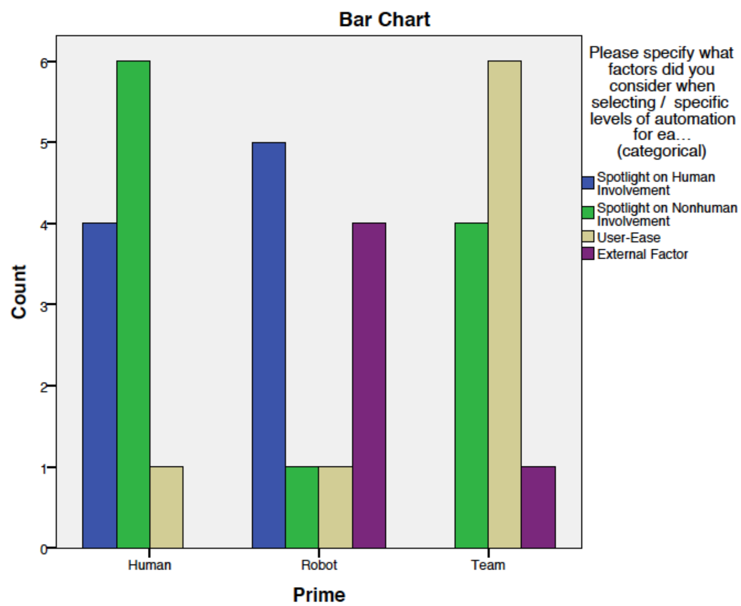

Figure 5: Results from a Chi Square Test for Association shows statistical significance between prime and levels of automation scaling. As shown, there is a difference between the categorical values within the levels of automation and the primes a participant was randomly exposed to.

Test Statistics[a,b]

	Analyzing all the legos	Organizing legos	Sorting legos into sub groups based on color	Sorting legos from sub groups into smaller groups based on size
Chi-Square	.130	.806	2.269	1.421
df	2	2	2	2
Asymp. Sig.	.937	.668	.322	.491

Test Statistics[a,b]

	Placing the small lego pieces in to the kit	Placing the large lego pieces into the kit	Rechecking if all the lego pieces are in the right places in the right amounts in the kit	Putting the kit away into storage
Chi-Square	2.434	1.787	.878	.753
df	2	2	2	2
Asymp. Sig.	.296	.409	.645	.686

a. Kruskal Wallis Test

b. Grouping Variable: Prime

Figure 6: Results from the Kruskal-Wallis Test are as shown above. The results lead to the interpretation that either there was not enough data to see if there was a difference in levels of automation scaling in the various sorting steps, or if there truly is not difference based on the prime.