

TELL ME YOUR FEELINGS: Characterization and Analysis of Human Comfort in Human-Robot Collaborative Manufacturing Contexts

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Abstract—Robotics technology has been widely utilized for multiple applications in recent years. Human comfort has a direct impact on task quality and efficiency during the human-robot collaboration process. As an emerging study, human comfort in human-robot collaboration attracts more and more attention of scholars. In this study, we propose a novel approach to characterize and analyze human comfort based on T-Test to advance the understanding of human factors for the future of smart manufacturing. A factor set of robot performance and work environments that affect human comfort in the human-robot collaboration process is developed. We implement the proposed method to a high-diversity group of participants who are from different educational backgrounds, ages, genders, and countries. Experimental results and analysis indicate that the comfort levels of subjects are effectively evaluated under different/same robot/work environment factors. In addition, the highly statistically significant factors that affect the participants' comfort level positively or negatively are discussed.

Keywords—Robotics, human-robot interaction, comfort, smart manufacturing, human factors

I. INTRODUCTION

Robotics technology has been increasingly employed in a range of application areas in recent years [1, 2]. Human-robot collaboration can be viewed as humans and robots working together on common tasks forming a team. A team can be defined as several companions with compatible skills that are aiming to reach the same goals, efficiently achieve the common purposes, and methods for which they consider themselves mutually responsible. This also applies to human-robot teams where the companions are humans and robots, aiming to reach the same objectives through collaboration [3-6]. Currently, most modern factories leverage human-robot collaboration as a part of their daily routine. Human-robot collaboration can be found not only in factories, but offices, hospitals, and even outer space [7-11]. Industries continue to develop and verify innovative solutions intended to improve upon current manufacturing processes. The new approaches, which focus on robots assisting and supporting humans, provide a safer, friendlier working environment, and increase efficiency [12].

This work was supported in part by the National Science Foundation under Grant CNS-2104742 and in part by the Montclair CSAM Faculty-Student Summer Research Program.

Thus, improving the human-robot relationship would increase cooperation and boost efficiency between humans and robots. In addition, improvements to the human-robot relationship would enhance the work environment tremendously by making it safer and more comfortable.

Human comfort during any human-robot collaborative work would help improve the task quality and efficiency [13, 14]. Introducing robots without considering human comfort during a task might result in poorly performed tasks as there would be a lack of seamless and efficient collaboration between the two sides. Furthermore, this will cause slower productivity, increase the possibility for error, and could even result in injury over longer periods. Another thing to consider would be its effect on creating a poor work environment. As human workers' dissatisfaction with tools and their robot counterparts rises, people may be less inclined to foster a better relationship. On the other hand, when human comfort is considered, the ergonomics will be improved and human partners will be more encouraged to maintain a better human-robot partnership, which will enhance both the task quality and the general work environment. Therefore, considering how much human comfort affects work efficiency, we can see how important human comfort in general is.

II. RELATED WORK

Several related studies have been conducted in recent years. An experiment conducted by the Department of Human Factors at Ulm University presented the impact of propensity to trust in automation and negative attitudes toward robots on state anxiety, trust, and comfort distance toward a robot [15]. Chen et al. developed four levels to plan muscular and peri personal-space comfort using the Baxter robot. This work included three steps: peri personal-space comfort is the step to develop a metric for human-robot teams. Stability checking is used for developing muscular and peri personal space comfort. Finally, the optimization process focuses on evaluating the performance of the combined optimization with four planners [16]. Another study that focused on an aspect regarding human-robot collaboration was carried out to evaluate the performance difference between using human-aware robots and robots with standard motion planning. Multiple tests such as Wilcoxon signed-rank test and the Shapiro-Wilk test were used in this

investigation [17]. Through experiments with operators in manufacturing lines, a study addressed several areas of architecture of human robot collaboration such as task planning, task representation, and allocation of tasks combined with movement planning and the natural collaboration of humans and robots [18]. Wei et al. did two experiments, in which directing ways and sorting objects were conducted to evaluate the expression emotion of robots' impact on the participants' perception about the robot [19].

However, there is still a lack of comprehensive understanding of robot/work environment factors (e.g., speed, human-robot proximity, or lighting condition) that may affect humans' comfort in human-robot collaborative tasks. Even though the experiments mentioned were about human-robot collaboration and some mentioned human comfort, but they did not focus on or study the factors, especially the highly significant factors, that affect human comfort directly during human-robot collaboration.

To this end, a T-Test based approach for characterizing and analyzing human comfort in human-robot collaborative tasks is proposed in this study. We develop a factor set with 21 elements of robot performance and work environments to investigate which factors have a higher influence or effect on human comfort during the human-robot collaboration process. The proposed approach is tested with a high-diversity group of participants. We compare these factors against the neutral state which serves as our reference point and discuss statistically significant factors that highly affect the participants' comfort.

III. APPROACHES

A. Human Comfort Conceptualizing

In human-robot collaboration, human comfort can be defined as a feeling of consolation, relief, or satisfaction caused by the factors of robot performance or work environments when the robot collaborates with the human to complete shared tasks [13]. Human comfort is a positive feeling that can be converted from a negative feeling (discomfort) or a neutral feeling when the human's unhappiness, anxiety, or tension is mitigated by the robot's proper assisting actions. To evaluate human comfort in human-robot collaboration, we need to measure the effect of robot actions or the work environment on human feelings. We should also concern the discomfort while evaluating human comfort. In this work, we will characterize human comfort by exploring multiple factors to determine if they help with human comfort or if they cause discomfort.

TABLE I. REWARD STRATEGY FOR THE CHARACTERIZATION OF HUMAN COMFORT

<i>Comfort Level</i>	<i>Reward</i>
Very Uncomfortable	-3
Uncomfortable	-2
Somewhat Uncomfortable	-1
Neutral	0
Somewhat Comfortable	1
Comfortable	2
Very Comfortable	3

B. Characterization of Human Comfort

While collecting data from participants in human-robot collaborative contexts, we develop a reward strategy to

characterize each comfort level from a Likert scale [20] with a number starting with zero as the neutral state and positive numbers for the feeling of comfort and negative numbers for the feeling of discomfort. As shown in Table I, we employ a 7-point Likert scale with numbers ranging from (-3) to (3). This characterization strategy allows us to quantificationally evaluate the human comfort levels we received from participants. For example, if most people feel one of the positive feelings towards a specific robot factor, this will result in a positive number for the corresponding comfort level. On the other hand, if most people feel negatively towards another robot factor, this will result in a negative number for the corresponding discomfort level. Taking the weight of each factor and its correlation to human comfort, the significance of the weights can be determined and tested against other results. Thus, we will further get how much each factor affects the participants' comfort.

C. T-Test

The T-Test is an inferential statistic, which is utilized to find out if there is a significant difference between the means of two groups that might have similar features. It is one of the tests utilized to examine hypotheses in statistics. Computing a T-Test needs three main data values including (1) the mean difference that is the difference between the means of both data sets, (2) the standard deviations of each data set, and (3) the number of values in each data set [21, 22].

Comparing the samples of group A and group B, the T-Test value can be evaluated as

$$t = (m_A - m_B) / \sqrt{\frac{S^2}{n_A} + \frac{S^2}{n_B}}$$

where m_A and m_B are the means of group A and group B, separately, n_A and n_B denote the sizes of group A and group B, respectively, and S^2 is an estimator of the pooled variance of the two groups. It can be expressed as

$$S^2 = \frac{\sum_{i=1}^{n_A} (x_i - m_A)^2 + \sum_{j=1}^{n_B} (x_j - m_B)^2}{n_A + n_B - 2}$$

with degrees of freedom (df) as $df = n_A + n_B - 2$, where x_i and x_j are samples of the group A and B, respectively.

We make four assumptions while using the T-Test. The first assumption for the T-Test is that the measurement scale applied to the data acquired follows an ordinal and continuous scale. The second assumption is that the sample of participants is from representative groups. The third assumption is that the result of the data is a normal distribution, bell-shaped distribution curve. The fourth assumption is only assumed if equal or homogeneous variance exists when the standard deviations of both data sets are approximately equal [23, 24].

TABLE II. AN EXAMPLE OF HUMAN COMFORT EVALUATION RESULTS OF THE FAR DISTANCE OF HUMAN-ROBOT PROXIMITY VIA T-TEST

<i>Parameter</i>	<i>Result</i>
Neutral states mean	0
Far distance mean	0.36
t value	1.8395
Degree of freedom	138
p value	0.068
critical value	1.976

In this study, using the neutral state as our base group and comparing it with our collected data for each factor, we can see if the factor has any effect on human comfort during the human-robot collaboration process. For example, if we take the data collected from the far distance of human-robot proximity and get the evaluation results as shown in Table II, where the calculated t value is smaller than the critical value. Hence the means of these samples are not significantly different, which indicates that having the robot work with its human partner from a far distance did not affect his/her comfort level enough to be statistically significant.

IV. EXPERIMENTAL SETUP

A. Experimental Platform

The experimental platform includes a collaborative robot, a target object, and a shared workspace. We assign a vehicle model co-assembly task to the robot and its human partner in manufacturing contexts. The robot used is Franka Emika, which is a 7-DoF collaborative robot [25]. During the human-robot co-assembly process, we change the robot performance and adjust the work environments with 21 factors to investigate their influence on human comfort. To conduct this study by recruiting a diverse participant body in the pandemic period, we create an online comfort evaluation platform. On this platform, we record a video in which the robot delivers parts to its human partner in the co-assembly task with 21 different factors of robot performance and work environments. The participants can take part in the experiment at home by watching the recorded video and rating their comfort levels on each factor via online synchronous questions.

B. Factors of Robot Performance and Work Environments

We investigate 21 factors that might affect human comfort during the human-robot collaboration process. These factors are listed in Table III.

TABLE III. THE FACTORS OF ROBOT PERFORMANCE AND WORK ENVIRONMENTS USED IN THIS STUDY

No.	Factor
1	Far distance
2	Medium distance
3	Close distance
4	High speed
5	Medium speed
6	Low speed
7	High robot delivery position
8	Medium robot delivery position
9	Low robot delivery position
10	Dim lighting and far distance (DLFD)
11	Dim lighting and medium distance (DLMD)
12	Dim lighting and close distance (DLCD)
13	Soft lighting and far distance (SLFD)
14	Soft lighting and medium distance (SLMD)
15	Soft lighting and close distance (SLCD)
16	Regular factory noise and far distance (RNFD)
17	Regular factory noise and medium distance (RNMD)
18	Regular factory noise and close distance (RNCD)
19	High factory noise and far distance (HNFD)
20	High factory noise and medium distance (HNMD)
21	High factory noise and close distance (HNCD)

C. Data Collection

The Mindstamp [26] is used for the development of our online comfort evaluation platform. It allows us to dynamically

create an interactive video survey and organize the data. The Mindstamp also allows us to make sure our data is coming from different participants by showing us duplicated views and the degree of completion for each viewer. In addition, we can control the flow of the video.

D. Participants

We collected data from 70 participants including 41 male participants (58.6%) and 29 female participants (41.4%) with different ages, educational backgrounds, and countries. Most of the participants are in the age range [20, 30], which is a representative group of future workforces. The participants include undergraduate students, master's students, Ph.D. students, technical college students, faculty, and others. Showing that it is more diverse than the age distribution. The participants are from 9 different countries, which makes our collected data substantially representative and solid. Through checking the IP addresses of the participants, each participant's view was counted once by us even if they rewatched the video.

V. RESULTS AND ANALYSIS

In this section, the results and analysis of the influence of human-robot proximity, robot speed, lighting condition, and noise in the work environment on the participants' comfort are presented.

A. Human-Robot Proximity

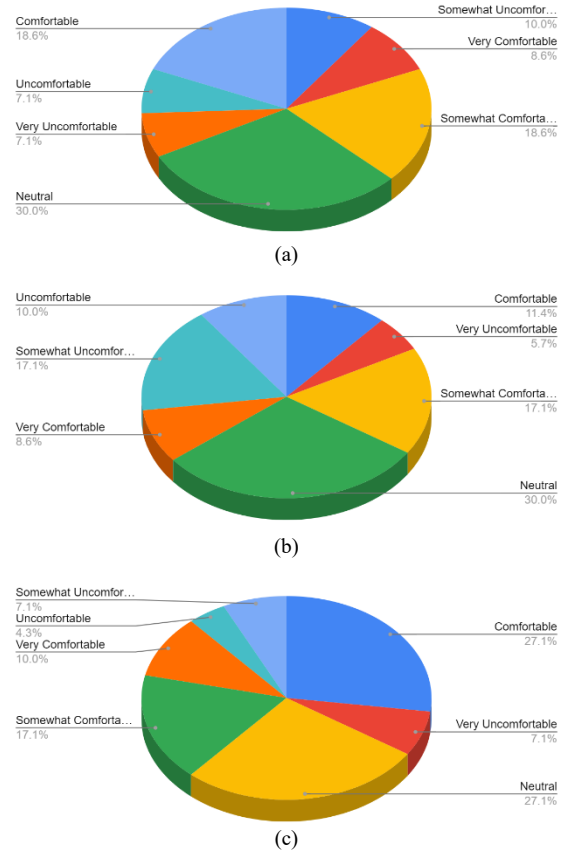


Fig. 1. Participants' comfort influenced by the human-robot proximity. (a) Far distance. (b) Close distance. (c) Medium distance.

The participants' comfort influenced by the human-robot proximity is shown in Fig. 1. We have 3 factors related to human-robot proximity. Fig. 1 (a) shows how participants felt when the robot handed an object to them from a far distance. After calculating the t value as 1.8395 and the p value as 0.068 of the comfort data, we concluded that the far distance is not statistically significant since the comfort data indicates that it did not affect the participants' comfort level enough to be statistically significant. In addition, when the robot handed our participants the object with close proximity. The participants' responses were mixed between somewhat uncomfortable and somewhat comfortable as shown in Fig. 1 (b). The evaluated t value is 0.6037 and the p value is 0.547. The close distance was also not statistically significant because the comfort data indicates that it did not affect the participants' comfort level enough to be statistically significant. On the other hand, as shown in Fig. 1 (c), the medium distance was very positive. After calculating the t value as 3.293 and the p value as 0.0013, we found that the medium distance is highly statistically significant because the results indicate that it did affect the participants' comfort level positively to be very statistically significant.

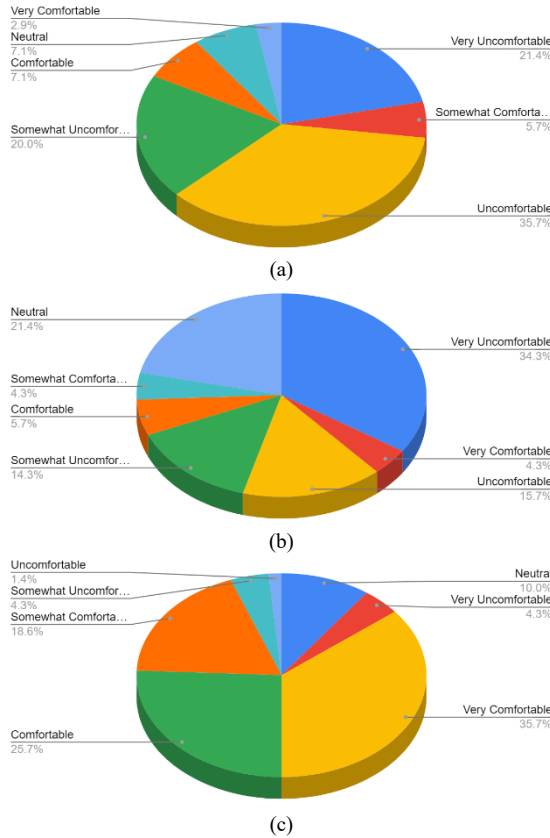


Fig. 2. Participants' comfort influenced by the robot speed. (a) High speed. (b) Low speed. (c) Medium speed.

B. Robot Speed

The participants' comfort influenced by the robot speed is shown in Fig. 2. We have 3 factors related to robot speed. Fig. 2 (a) shows how participants felt when the robot handed an object to them at high speed. After calculating the t value as

6.6259 and the p value as 0.0001 of the comfort data. We concluded that the high speed is extremely statistically significant. The comfort data indicates that the high speed affected the participants' comfort level in an extremely negative way which can also be deduced from Fig. 2 (a) since the overwhelming majority had negative responses. In addition, when the robot handed our participants the object with low robot speed. The participants' responses were also very negative as shown in Fig. 2 (b). The results ($t = 5.685$ and $p = 0.0001$) suggest that the low robot speed did affect the participants' comfort level enough to be extremely statistically significant. On the other hand, as shown in Fig. 2 (c), the medium robot speed was overwhelmingly positive. After calculating the t value as 8.3481 and the p value as 0.0001, we found that the medium robot speed is extremely statistically significant because it did affect the participants' comfort level positively to be very statistically significant.

C. Lighting Condition

The participants' comfort influenced by the lighting conditions is shown in Table IV. We have 6 factors related to lighting conditions. For the soft lighting condition, after calculating the soft lighting and far distance against the far distance and finding the t value as 0.9247 and the p value as 0.3567, we concluded that it was not statistically significant. The results indicate that, in all three cases of soft lighting against distance (far, medium, and close), the participants were not affected enough to be considered statistically significant. On the other hand, when we tested dim lighting conditions for far distance ($t = 6.6813$ and $p = 0.0001$), medium distance ($t = 5.7717$ and $p = 0.0001$), and close distance ($t = 5.0158$ and $p = 0.0001$). Against the three kinds of distances in a well-lit room, we found that our participants had an overwhelmingly negative response for all three dim lighting cases. The results suggest that the dim lighting condition is extremely statistically significant. Therefore, we should avoid creating such a work environment when we develop and deploy human-robot collaborative contexts.

TABLE IV. PARTICIPANTS' COMFORT INFLUENCED BY THE LIGHTING CONDITION

	DLFD	DLCD	DLMD	SLFD	SLCD	SLMD
Very Uncomfortable	24.3%	25.7%	12.9%	4.3%	2.9%	5.7%
Uncomfortable	32.9%	22.9%	31.4%	11.4%	8.6%	11.4%
Somewhat Uncomfortable	18.6%	21.4%	22.9%	15.7%	5.7%	14.3%
Neutral	11.4%	14.3%	11.4%	27.1%	30%	24.3%
Somewhat Comfortable	8.6%	10%	11.4%	25.7%	20%	20%
Comfortable	2.9%	4.3%	8.6%	10%	27.1%	18.6%
Very Comfortable	1.4%	1.4%	1.4%	5.7%	5.7%	5.7%

D. Noise in the Work Environment

The participants' comfort influenced by the noise in the work environment is shown in Table V. We have 6 factors related to noise in the work environment. For regular factory noise, after calculating the regular factory noises and far distance against the far distance and finding the t value as 2.6529 and the p value as 0.0089, we concluded that it was statistically significant. The results indicate that it affected the participants' comfort level negatively. In the other two cases of regular factory noises in the work environment against distance,

the participants were not affected enough to be considered statistically significant. On the other hand, when we tested high factory noises in the work environment for far distance ($t = 6.5304$ and $p = 0.0001$), medium distance ($t = 7.4468$ and $p = 0.0001$), and close distance ($t = 5.7133$ and $p = 0.0001$). Against the three kinds of distances in a quiet room, we found that our participants had an overwhelmingly negative response for all three high noise cases. These results indicate that the high factory noise is extremely statistically significant. Therefore, we should avoid creating such a work environment when we develop and deploy human-robot collaborative contexts.

TABLE V. PARTICIPANTS' COMFORT INFLUENCED BY THE NOISE IN THE WORK ENVIRONMENT

	RNFD	RNCD	RNMD	HNFD	HNCD	HNMD
Very Uncomfortable	10%	14.3%	8.6%	27.1%	31.4%	18.6%
Uncomfortable	15.7%	17.1%	12.9%	30%	28.6%	40%
Somewhat Uncomfortable	18.6%	18.6%	10%	14.3%	14.3%	14.3%
Neutral	28.6%	12.9%	20%	15.7%	12.9%	12.9%
Somewhat Comfortable	11.4%	21.4%	22.9%	8.6%	5.7%	10%
Comfortable	14.3%	11.4%	24.3%	2.9%	4.3%	2.9%
Very Comfortable	1.4%	4.3%	1.4%	1.4%	2.9%	1.4%

VI. CONCLUSIONS AND FUTURE WORK

In this study, we have proposed a T-Test based approach to characterize and analyze human comfort for human-robot collaboration in manufacturing contexts. We have employed 21 factors of robot performance and work environments to investigate which ones have a higher influence or effect on human comfort during the human-robot collaboration process. The proposed solution has been experimentally implemented to a high-diversity group of participants. Results and analysis suggest that the comfort levels of subjects are effectively evaluated under different/same robot/work environment factors. In addition, we have also discussed the factors, which are highly statistically significant, that affect the participants' comfort level positively or negatively. Based on these preliminary findings, in our future work, we will create a novel computational model to dynamically evaluate human comfort levels during the human-robot collaboration process.

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