How Are You Feeling?: Characterization and Analysis of Human Factors in Multi-Human Multi-Robot Collaborative Tasks

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***Abstract*—Collaborative robots have been employed in a wide range of applications across industries, especially as the transition continues into Industry 5.0. As this new industrial revolution occurs, human-centricity becomes an ever-increasing focus, and the need for a developed understanding of how robot behaviors affect the fundamental human factors of trust, comfort, and acceptance in human-robot collaborative contexts grows. While many efforts have been conducted in this area, what remains relatively understudied on this topic is when robots are working with human workers in a Multi-Human Multi-Robot (MHMR) environment. In this work, we present a framework and develop an experimental platform to collect humans' multimodal physical and physiological biometrics information in order to characterize human factors in MHMR interaction. The electrocardiograms, galvanic skin response, pupillometry, and electromyography signals are acquired during the MHMR collaborative manufacturing process. Experimental results and analysis suggest that human workers' responses to different robot behaviors can be dynamically and quantitatively characterized in MHMR collaboration. This work is a cornerstone for further modeling and understanding of human factors (e.g., trust, comfort, and acceptance) to improve collaboration efficiency for MHMR partnerships in Industry 5.0 contexts. Future directions of this study are also discussed.**

***Keywords*—Trust, robotics, human factors, safety, human-robot collaboration, physiological biometrics**

I. Introduction

It is unsurprising that the application of robots in industry has seen tremendous growth within recent years, spanning across the healthcare, manufacturing, and agriculture sectors, in addition to others [1-3]. Facilitated by the rise of Industry 4.0, the number of operating industrial robots around the world surpassed 4 million as recently as 2023 and continues to rise in annual installations [4]. The Industry 4.0 paradigm brought with it the introduction of cyber-physical systems, big data, and Internet of Things, which permitted the development of intelligent production environments driven by robotics, AI, and sensors designed to enhance the safety of workers within these spaces operating both around and with autonomous systems [5].

The robots that function with operators in a shared space are known as collaborative robots or cobots [6]. Collaborative robots are an intriguing component of modern smart factories, especially with consideration for the approaching Industry 5.0, which is more value-driven than technology-driven and has a large human-centric focus in addition to other values such as sustainability and resilience [7]. That being said, ensuring collaborative robot systems that work alongside human workers are acceptable as well as capable is critical to Industry 5.0. This acceptability extends to the ideas of trust and comfort when interacting with the robot as well, as high levels of these factors are beneficial to any type of collaborative interaction. Generally, research into these factors in human-robot collaboration is examined in single-human single-robot contexts.

Making such investigations in multi-human multi-robot (MHMR) environments provides a unique challenge, and most studies rather focus on task allocation and performance metrics of the team [8]. However, some studies have sought to model and evaluate trust in such settings, such as [9], which presents an expectation confirmation trust model. This model involves concepts including initial trust and expectations, among others. The evaluation of trust is necessary to the research area of collaborative robotics, and the same for the factors of comfort and acceptance [10-12]. These three factors are some of the primary subjects of extensive observation in human-robot interaction (HRI) [13, 14]. Enabling effective collaboration and teamwork demands high levels of trust between cooperating parties, comfort with working alongside them, and acceptance of them in their work. Typically, these factors are evaluated on a subjective level according to responses gathered from surveys issued either during or after an interaction. While this approach is effective, it leaves room for potential inaccuracies for several possible reasons, including misunderstanding questions. That being said, they are still capable of providing valuable insights into the feelings of those interacting with the robot.

An alternative method of evaluating these factors exists in the form of using sensors to collect physical and physiological signals that may represent a particular emotional or mental state. Such signals typically include electrocardiogram (ECG), skin temperature, electrodermal activity (EDA), respiratory activity, electromyography (EMG), and electroencephalography (EEG) [12, 15]. Bethel *et al*. noted that, among four identified evaluation methods in HRI studies, including self-report measures (surveys), behavioral measures, psychophysiology measures, and task performance, none of these alone is sufficient to provide a comprehensive interpretation of interactions between the human and the robot [16].

In this study, we present an experimental foundation for evaluating the human factors of trust, comfort, and acceptance felt by users when interacting in multi-human multi-robot collaborative contexts with dynamic robot performance conditions, including variations in speed and handoff positions. Establishing the ideal parameters for which the robot will operate to ensure user comfort and trust is crucial for developing more human-centered systems, especially due to the natural implications of creating adaptable robots that can actively shift their behavior to accommodate user preferences in real-time. In our experiments, subjects' physical and physiological data are collected during the interaction for the purpose of creating a database that may be used to extrapolate conclusions regarding these human factors. That is, how the robots' speed, handoff distance, and handoff height affect these factors. Studies such as these in MHMR contexts are relatively underrepresented in the community, and the purpose of this work is to attempt to mitigate that gap. This work is also a cornerstone for further modeling and understanding of human factors to improve collaboration efficiency for MHMR partnerships in Industry 5.0 contexts.

II. Related Work

MHMR environments are a challenging setting to research human factors since operators are not working with just one robot, but with potentially multiple in addition to human teammates. Additionally, the idea that basic one-to-one HRI is scalable regarding human factors has likely led to a noticeable gap in this area. Existing research focus in the field of MHMR interaction takes a few forms. For instance, Malvankar-Mehta *et al*. presented a multi-level programming model for such an environment with the objective of optimally allocating tasks to team leaders and therefore maximizing system performance and minimizing processing cost and time [8]. This model also takes into account human factors. More specifically, operator-specific workload and cognitive thresholds. Naturally, the human operators are the primary focus of this type of research, and as more are introduced, more issues arise that must be considered. Patel *et al*. addressed such an issue that is defined as the "out-of-the-loop performance problem," which is caused by a lack of engagement in the task, awareness of its state, and trust in the system and other operators [17]. The problem is not one that is unique to MHMR systems, but is one that certainly becomes more prevalent in such environments. The work detailed the creation of the first mixed granularity interface for MHMR interaction that was evaluated by workload, trust, and task performance.

It is noted that low-level granularity of control (GOC) in systems such as these offers more opportunity for interaction and development of trust in the system at the expense of potentially higher workload and stress, whereas high-level control limits the workload but also may lead to boredom and lower situational awareness [18]. Our work seeks to avoid this problem while also providing users with more opportunities for trust development by giving very low levels of GOC. This will permit a more accurate assessment of human factors when interacting with the system, as they will be actively engaged in its operation. In contrast to the lack of research into the MHMR setting, there exists literature on the use of physiological biomarkers for assessing such factors. Be it for emotion recognition and inference [19], trust assessment [12], or comfort [20], these markers provide a window into the mental state of a person that may be examined to gain a clearer understanding of how certain external factors affect their mood.

The evaluation of trust, comfort, and acceptance based upon varying robot behaviors, especially through the analysis of physical and physiological markers, is a topic that does not appear to be heavily investigated in MHMR environments. While existing work in this domain has considered human factors, these three have yet to be comprehensively analyzed together. We seek to do so to study and establish how the shift from single-human single-robot interaction changes when human operators are placed into the workspace with other workers and multiple robots with varying behaviors.

III. Multimodal Physical and Physiological Biometrics Data

A. ECG

Electrocardiograms are a measurement process that measures the electrical activity of the heart. From these readings, it is possible to obtain heart rate bpm and RR-interval metrics, which can be used as indicators of cognitive or emotional state. As such, studies have examined the use of this data for the assessment of trust, comfort, the general emotional state, and their attitude of acceptance [21]. It should not be ignored that the heart is well connected to the sympathetic and parasympathetic nervous system, which are directly responsible for the "fight-or-flight" and "rest-and-digest" responses, respectively [22]. The myelinated vagus nerve, or "vagal brake," inhibits the threat-defensive behaviors associated with the sympathetic nervous system, which promotes a calm physiological state. When safety is threatened, the vagal brake releases and permits the sympathetic nervous system to take over. The balance of these two systems is what produces variability in heart rate (HRV) as sympathetic speed ups transition into parasympathetic braking, and vice versa [23]. This variation in heart rate may be used to assess the stress and comfort that may be felt during MHMR interaction, as low HRV is associated with high sympathetic arousal, and high HRV with high parasympathetic arousal.

B. GSR/EDA

Galvanic skin response (GSR) is a psychophysiological signal that is modulated by the sympathetic nervous system. Arousal is indicated by the conductivity of the surface of the skin, which may be used to assess stress, emotional response, and cognitive load [24]. As it is placed on the surface of the skin, most GSR sensors are non-obtrusive and do not obstruct normal function. Furthermore, studies have employed the use of these sensors for the purpose of estimating trust and comfort [20, 25]. As such, we make use of this data in our study as well.

C. Pupilometry

Pupillometry is the measurement of the changes in pupil diameter, which often occur in response to stimuli. Such stimuli can often be attributed to cognitive load, emotional variation, or arousal [26]. These changes can be examined at the time of the stimulus to ascertain the reason for them, based on which studies have been done to assess comfort and trust [27]. Our study collects this data for further analysis in MHMR collaborative contexts.

D. EMG

Electromyography is the process of recording the electrical activity produced by muscles. Higher stress is typically associated with greater muscle activation, especially in the forearm [28]. Thus, we make use of this data in our examination of potential stress in MHMR environments, which may in turn be used to draw conclusions regarding trust, comfort, and acceptance.

IV. Experimental Setup

A. Experimental Platform

Our MHMR collaborative experiments are conducted on the Multimodal Collaborative Robot System (MCROS) [6], which is designed and developed to facilitate human-robot research and applications. As shown in Fig. 1, the MCROS has two UR10e arms, a mobile base, and a suite of sensory systems including 3D LiDARs, force-torque sensors, GPS, panoramic cameras, and more. The Robot Operating System (ROS) is used for MCROS programming and control, which empowers it to be an open-source system to seamlessly integrate with other cyber-physical systems in different tasks [29].

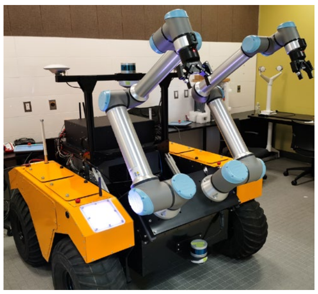


Fig. 1. The MCROS.

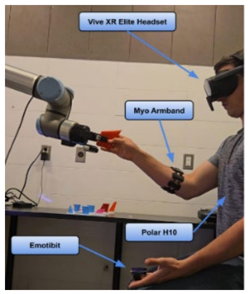


Fig. 2. Sensor setup.

B. Sensors

Four types of sensors are used in our experiments to collect the ECG, GSR, Pupillometry, and EMG data. The first is the Polar H10 heart rate sensor, which is a wireless ECG device and requires direct contact with the skin to conduct its measurements. Testing has shown a high degree of accuracy of its data [30]. GSR data is collected using an Emotibit sensor, a device capable of recording EDA, PPG, temperature, and motion. Much like the Polar H10, experiments have shown a very high degree of accuracy of the measurements taken with the device [31]. As such, we employ it in our study for measuring GSR/EDA signals. The sensor is placed on the subject's non-dominant ring finger. Eye gaze data is collected using the Vive XR Elite headset. This headset is capable of tracking the eye position and rotation (X, Y, Z), pupil diameter, pupil position, and eye openness for both the left and right eyes. While all of this data is collected during the study, our primary focus is the pupil diameter measurements, though other data may be used for the extrapolation of blink frequency as well. The final sensor that we employ in this study is the Myo armband. This sensor is capable of tracking EMG signals over 8 channels and is worn on the upper forearm. When placed, the muscles covered are the flexor digitorum superficialis, extensor digitorum, brachioradialis, extensor digiti minimi, extensor carpi radialis longus, and extensor carpi ulnaris [32]. Fig. 2 shows the sensor setup for each participant in our study.

C. Task Description

In our experiments, human participants will work with robots to complete a collaborative assembly task. As presented in Fig. 3, the product to be assembled is a plane model that includes 18 separate parts. Each arm of the MCROS is assigned to a user, who will work with their partner to assemble the full model. As shown in Fig. 4, each side is responsible for assembling a wing (red/green), a fuselage (white/blue), and a stabilizer (pink/yellow), so the distribution of tasks between the two participants is equivalent. The robots retrieve the parts from the workspaces on each side and hand them off to their operators at varying heights and distances. The experiment is run twice, first with the robots moving at high speed, and next at low speed. Each trial includes 9 different robot behaviors as described in Section V.

Fig. 3. The collaborative assembly task.

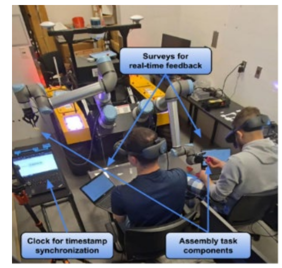


Fig. 4. The MHMR experimental setup.

A laptop with a survey is provided in front of each user so that they may respond in real time, rating their perceived trust, comfort, and acceptance of the robot given its most recent action. After each handoff movement, the robot will pause for 30 seconds to provide time for the operator to fit their parts together as well as answer the three questions associated with the movement. After each trial, a TLX questionnaire is to be filled out prior to moving on to the next.

Synchronization of timestamps is critical to the data collection and analysis process. Each arm's movements and activity are recorded with a timestamp at one-second intervals throughout the experiment, and this enables necessary insight into what stimulus causes the physiological responses that are produced. A global clock and time synchronization are used to ensure that all timestamps line up properly. Following the assembly of each participant's task, they may turn to each other to finish the process together. We include this part of the experiment to directly compare the physiological responses of the collaborating pair to those experienced during their interaction with the robot.

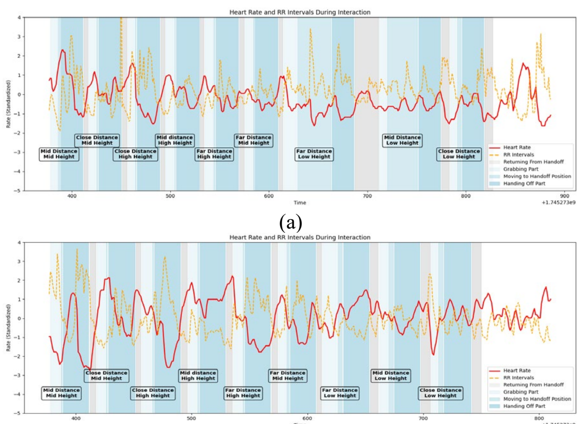
D. Data Collection

Our data is collected firstly from the sensors that participants wear during the interaction, and secondly from their own subjective measures of their trust in the robot, comfort with its actions, and overall acceptance of it. Prior to beginning the experiment, it is crucial that they have a firm understanding of what these categories mean. Thus, we adhere to the following definitions.

Trust in HRI involves an expectation or attitude regarding the likelihood of favorable responses. Jin-Hee *et al*. present trust as the willingness of a trustor to take a risk based upon their belief that the other party (trustee) will act reliably to maximize the trustor's interest under uncertainty of a situation based on the cognitive assessment of prior experience with the trustee [33]. We adhere to this definition for the purpose of our study. Comfort and acceptance are more easily defined. Most people are capable of providing a subjective rating of their comfort at a given moment or with a given scenario. Their ratings, paired with the physiological data to be collected, are more than sufficient to measure their sense of ease. Similarly, most people are able to indicate their level of acceptance of a partner–be it human or robot. Idle time, speed, fluency, and efficiency are all contributors to levels of acceptance [34], and are expected to be taken into account by participants of this study.

The survey that participants are presented with is to be completed in part before and in part during the experiment while interacting with the robot. Prior to starting, it first asks questions regarding the participant's demographics, such as age, sex, education, previous experience with robots, attitude towards robots, and their familiarity with their partner. Much of this data is collected to uncover potential biases and relationships in responses during the MHMR collaboration. These responses ask the participant for their subjective rating of trust, comfort, and acceptance for each behavior. After each trial of 9 robot movements, a TLX survey is provided. As shown in Fig. 5, a nine-point Likert scale is used to collect the ratings of human factors from participants.

Fig. 5. The Likert scale employed in MHMR collaboration.



(a)

(b)

Fig. 6. Heart rate and RR-interval variation of human participants in MHMR collaboration. (a) Participant A. (b) Participant B.

V. Experimental Results and Analysis

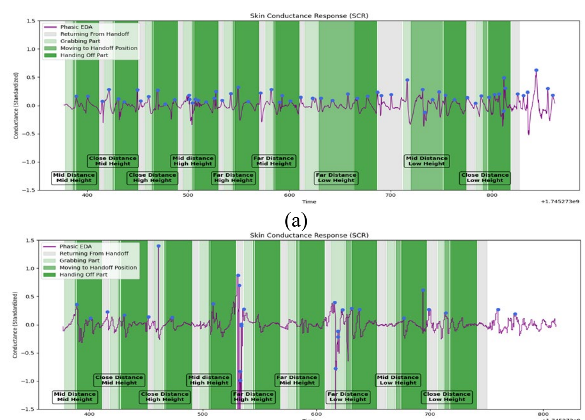
A. ECG Data and Analysis

Fig. 6 shows the variation of ECG signals from the two participants in the experiment. The charts provide a visual representation of heart rate and RR-intervals, both standardized, over the course of the interaction with the robot operating at high speed. Shaded regions are used to show what action the robot is performing at each point as well as the handoff position type used. Examining Fig. 6(a), it appears that early in the interaction, participant A experiences higher heart rate peaks and as expected, inverse RR interval dips. These peaks trend towards being both less prominent as well as more stable as the interaction continues, especially once the robot begins to hand off parts at low positions. This seems to indicate a higher degree of comfort as the interaction progresses, with a slower and more stable heart rate arriving with time. Even so, the RR-interval curve demonstrates some irregularities, suggesting a higher level of arousal. Fig. 6(b) exhibits high and consistent variability in the heart rate of participant B throughout the session without stabilizing. Close and high handoff positions appear to be associated with sharp increases in heart rate, and no downward trend is observed. This participant seems to be reactive, with no signs of habituation.

Comparing the two participants' ECG data, several observations may be made. Firstly, close and high positions seem to be correlated with greater peaks in heart rate, which indicates a higher degree of arousal and potentially stress. Additionally, as expected, heart rate decreases in a return to baseline during less demanding phases, such as when the robot is moving to acquire the next part. Participant A, however, seems to habituate to their task, becoming less reactive to stimuli as the experiment continues, while participant B remains comparatively responsive throughout.

B. EDA/SCR Data and Analysis

Fig. 7 shows the skin conductance response signals for the same two participants during the experiment. Like Fig. 6, shaded regions are used along with captions to show what action the robot is performing at a given point. The phasic EDA pattern observed in Fig. 7(a) is both moderate and consistent. Towards the end of the collaboration, the amplitudes increase slightly, indicating a mildly more intense response from participant A. These results are consistent with those observed from Fig. 6(a), with the same subject eliciting stability and habituation, suggesting moderate cognitive engagement of participant A in the MHMR collaboration. The SCR response of participant B shown in Fig. 7(b) is in line with the behavior observed in Fig. 6(b), demonstrating more extreme spikes, if less frequent peaks. These infrequent peaks would seem to indicate more selective engagement and arousal throughout the experiment.



(a)

(b)

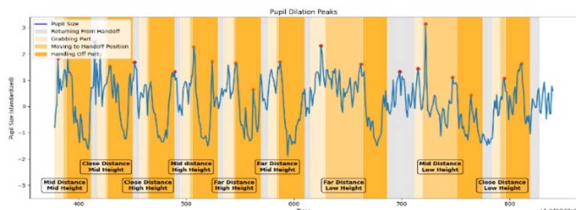
Fig. 7. SCR variation of human participants in MHMR collaboration. (a) Participant A. (b) Participant B.

It can be seen that participant A appears to maintain moderate and consistent arousal levels throughout the MHMR collaboration, while participant B is often highly reactive but less predictable. The response of Participant A could be attributed to comfort with mild stress and routine focus. These differences in responses highlight the varying levels of comfort and familiarity that people may have when working with collaborative robots.

C. Pupilometry Data and Analysis

Fig. 8 presents the pupil dilation variation of human participants in MHMR collaboration. Similar to Figs. 5 and 6, it uses shaded regions to indicate robot activities during the collaboration. The pupil dilation of each participant over the course of the interaction is depicted with red dots to mark peaks. Fig. 8(a) shows frequent and strong fluctuations in the pupil size of participant A throughout the task, especially during handoff sequences. It indicates sustained arousal or engagement of this participant from start to end. This is in line with the SCR responses observed from Fig. 7 (a), which could be associated with mild stress or routine focus. Fig. 8(b) demonstrates that participant B's behaviors are consistent with strong initial arousal and attention, which drops off as the experiment progresses. This could be attributed to a multitude of factors, including habituation, loss of engagement, or fatigue.

While participant A performs sustained reactivity, engagement, and sensitivity to the task, participant B only does so for the first half of the experiment. In both cases, however, handoff phases are nearly always associated with dilation peaks of varying sizes, which can be used to indicate relative arousal for varying robot behavior.



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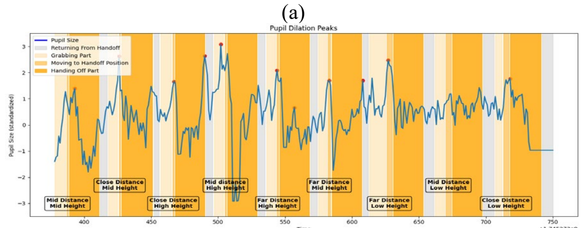


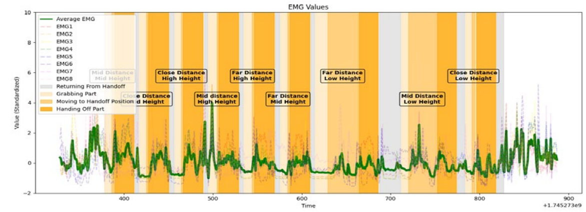
(b)

Fig. 8. Pupil dilation variation of human participants in MHMR collaboration. (a) Participant A. (b) Participant B.

D. EMG Data and Analysis

Fig. 9 shows the EMG values of the participants' arms throughout the experiment. As before, robots' activities are presented alongside these values, including an average, which can be used to uncover potential stressors during MHMR collaboration. Peaks are to be expected at the time of receiving parts by humans from robots, but the relative size of these peaks, as well as the values at rest, should be considered since they may indicate relative muscle tension that may reflect the stress of humans in the collaboration process with robots.

Fig. 9(a) uncovers potential stressors of participant A. It can be seen that most phases in which the part is received correspond to higher EMG values in the arm. Additionally, during periods between handoffs when human participants would expect a more relaxed state, the values hover above zero. This slight increase over baseline muscle tension could be attributed to sustained arousal, stress, or simply anticipation, which fits with participant A's behavior observed in other physical and physiological responses. Fig. 9(b), by contrast, shows lower EMG baselines during rest periods, and spikes similar in size to those observed in Fig. 9(a). As noted, baseline muscle tension could be attributed to arousal, stress, or anticipation. From this result, it would seem that these states are comparatively lower, with resting values falling into the negative standardized range.



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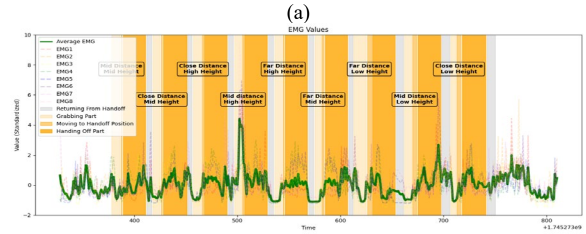

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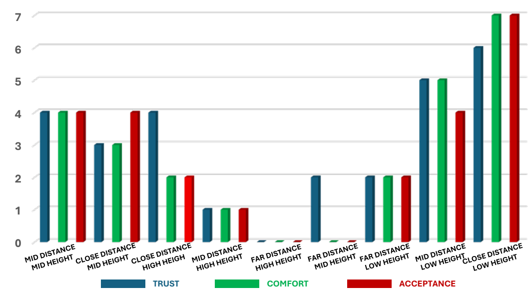
Fig. 9. EMG variation of human participants in MHMR collaboration. (a) Participant A. (b) Participant B.



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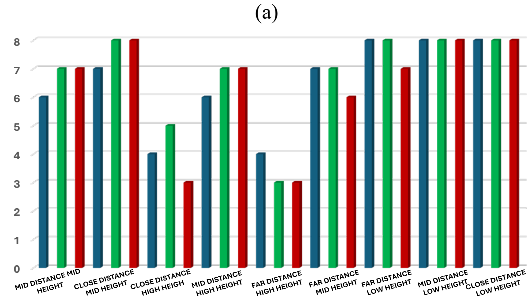

(b)

Fig. 10. Ratings of human factors in MHMR collaboration. (a) Participant A. (b) Participant B.

E. Human Factors Evaluation and Analysis

Participants' ratings of their trust, comfort, and acceptance for robot behaviors at high speed during the MHMR collaboration process are shown in Fig. 10. It can be seen that the levels of human factors of the two participants are quite different in relation to even the same collaborative task. For example, when robots deliver objects to their human partners from a greater distance, one of the participants feels more comfortable with the robot than the other one, perceiving the "far distance" as safer compared to situations where the robot comes too close. In addition, each participant presents varying levels of trust, comfort, and acceptance toward different robot actions throughout the whole collaboration process. For each robot action, a participant's trust, comfort, and acceptance are not always positively correlated. For instance, even if a participant accepts a robot's collaborative action during a shared task, they may still experience discomfort or lack full trust in the action. These findings imply that human factors in response to various robot behaviors during MHMR collaboration can be effectively characterized using dynamic and quantitative measures.

VI. Conclusions and Future Work

In this work, we have presented a framework to gather physical and physiological data regarding trust, comfort, and acceptance of participants as they interact with robots in a multi-human multi-robot environment. Investigations such as these in MHMR contexts are relatively underrepresented, and this work aims to alleviate that gap. By utilizing ECG, EDA, Pupillometry, and EMG data, we aim to identify what types of robot behaviors have what effects on what human factors in MHMR collaboration. Experimental results indicate that participants' responses to diverse robot behaviors can be dynamically and quantitatively characterized.

This work creates a catalyst to further computationally model and understand human factors for MHMR partnerships to improve collaboration efficiency in Industry 5.0 contexts. In addition to deeper forms of correlation analysis for the collected physiological data and human trust, comfort, and acceptance, we will conduct an extensive investigation, especially into how to build an explainable, trustworthy, comfortable, and acceptable multi-human multi-robot collaboration process and system for human workers in industry sectors. To address these issues, artificial intelligence and machine learning methods such as Transfer Learning [35], and Federated Learning [36] will be used for the collected data to reason and predict human factors such as trust, comfort, acceptance, emotions, and more in MHMR collaborative tasks. Additionally, we will design a comprehensive user study by hiring more participants to collect human factors-related information and evaluate our developed approaches.

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