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Effects of robot arm design and movement speed during human-robot interaction

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ABSTRACT

The purpose of this experiment was to investigate the effect of robot arm size, movement speed, and degrees of freedom on perceived safety, trust, mental workload, human behaviors, and task performance in a collaborative pick-and-place task. Fifty-six participants completed the experiment in a virtual reality environment where they interacted with a robot manipulator. Robot arm speed had a greater impact on self-reported measures, compared to task performance and human behavior. Overall, mean ratings of surprise and fear significantly increased across speed levels of 60 deg/s (surprise = 1.19/6; fear = 1.18/6), 120 deg/s (surprise = 1.37/6; fear = 1.33/6), and 180 deg/s (surprise = 1.65/6; fear = 1.67/6). Conversely, robot arm size and degrees of freedom had a greater influence on task performance and human behavior than on the self-reported outcomes. These findings may provide insights for robot manufacturers and standard committees to improve perceived safety in the workplace.

1. Introduction

Industrial robots have become a significant part of the industrial workplace. In 2023, more than four million industrial robots were being operated globally, with 12 % average annual increases since 2018 (Müller, 2024). Newer types of industrial robot arms are designed for human-robot interaction (HRI) in shared work areas. Human-robot interaction has the potential to enhance performance and working conditions substantially in various aspects compared to operations with traditional robots (De Simone et al., 2022). Implementation of these newer types of industrial robots may introduce unforeseen hazards or exacerbate existing risks due to workers' initial experiences working in dynamic human-robot collaborative work environments. For instance, in traditional robotic workplaces, physical barriers are typically placed to protect workers from potential injuries by preventing unintended contact with caged industrial robots. However, with industrial robots designed for collaborative operations, both intended and unintended physical contact between workers and robots can occur within a shared workspace, consequently increasing worker injury and fatality risk associated with physical contact with robots (Layne, 2023; Tan et al., 2009).

Robots operating within the personal space of a human worker may affect perceptions and subjective workload in those who share a space with robots (Johnson et al., 2019; Stark et al., 2018). Specifically, perceived safety, the user's subjective perception of the level of danger, is considered one of the critical components of safety in HRI, extending beyond the physical safety and cyber security involving robot use (Akalin et al., 2023). Existing HRI models and taxonomy indicate that perceived safety in HRI is closely related to several factors, including comfort and trust, which are influenced by robots' performance and attributes (Akalin et al., 2023). Perceived safety plays a critical role in building trust and influencing human behaviors around robots. For example, a previous study showed that people lowered their walking speed in the presence of a robot (Chen et al., 2018), suggesting safety-related behaviors may change in a collaborative robotic work environment. A higher perceived risk could lead to other behavioral changes, such as maintaining larger separation distances, more hesitation, and slower movements. Thus, changes in perceived safety and associated behavioral responses can result in ineffective collaboration and poor worker productivity. A sudden change in movement relative to the robot may also directly increase collision risks or raise potential human-robot contact forces to levels that may cause more severe injuries. Additionally, workers who feel unsafe may be more susceptible to distractions, leading to slower task execution or human error.

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Furthermore, higher perceived risks toward robots could increase worker stress and mental workload (De Simone et al., 2022), negatively affecting worker performance, health, and well-being.

In a taxonomy of factors influencing perceived safety in HRI, Akalin et al. (2023) specify critical physical, functional, and social properties and movement of robots that influence perceived safety, which includes physical appearance, size, speed, and motion trajectory. Common types of robots designed for collaborative operations consist of an arm-like manipulator mounted on a fixed base. The arm can have multiple joint axes that determine the movement flexibility (i.e., degrees of freedom), and an end-effector (i.e., tool) attached to the end that may vary in physical attributes, capabilities, and movement styles. The size of a robot arm is defined by several physical characteristics including the reach length (e.g., maximum distance from the robot's base to the end-effector when fully extended), the payload capacity, and the base footprint. Moreover, certain characteristics can periodically change during operation; for instance, a robot's movement speed or path may change as it adapts to situational task demands or the types of objects being handled during operation (Koppenborg et al., 2017). Past research has shown that a range of a robot's physical, movement, and communication characteristics can influence the user's perceived safety, trust, and robot acceptance and impact their behavioral and physiological responses (Rubagotti et al., 2022).

Specifically, previous studies have primarily focused on investigating the effects of proximity- and movement-related characteristics of robots, such as moving speed, stopping distance, and predictability, which are the attributes that commonly vary among industrial robots. These studies found that faster movements resulted in lower perceived safety, increased anxiety and workload, and that highly variable movements (e.g., sudden changes in speed) led to feelings of unsafety and distrust (Akalin et al., 2022; Bergman and Zandbeek, 2019; Chen et al., 2018; Hald et al., 2019; Koppenborg et al., 2017; Šlajpah et al., 2021; Story et al., 2022; Weistroffer et al., 2013). A few studies also demonstrated that a robot's appearance and size affect the user's acceptance and perceptions (Gervasi et al., 2024; Weistroffer et al., 2013). However, only a few limited robot attributes have been examined for their effects on human perceptions and behaviors during HRI, which also led to inconsistent findings (Rubagotti et al., 2022). Moreover, most previous studies examined each attribute independently and did not explore interactions between multiple physical and movement characteristics.

The current study examined the effects of the physical and movement characteristics of a robot on perceived safety, trust, mental workload, human behaviors, and task performance during HRI in an immersive virtual reality (VR) Cave Automatic Virtual Environment (CAVE) that simulated a manufacturing pick-and-place work task. Virtual reality simulation offers a cost-effective and safe method to study HRI in a controlled environment (Atkinson and Clark, 2014; Mitchell et al., 2020; Weistroffer et al., 2013). Previous studies demonstrate that VR can elicit perceived safety and safety-related behaviors comparable to those observed during HRI with physical robots, suggesting that VR is a valid alternative (Mitchell et al., 2020; Sanders et al., 2023). Specifically, this study examined the effects of two critical physical attributes – size and movement speed – and the degrees of freedom (i.e., number of axes of rotation), which is an under-researched movement characteristic, and their interactions. We hypothesized that robot arm size, movement speed, and degrees of freedom will influence perceived safety, trust in the robot, mental workload, task time, and participant hand speed.

2. Methods

2.1. Participants

Fifty-six (56) adults (29 males and 27 females) from the general population of Morgantown, WV in the U.S., participated in the experiment. The mean (SD) age of the participant sample was 24.8 (7.3) years. All participants reported being healthy, having normal or corrected to normal vision and hearing, not prone to nausea from VR experiences, and had current or prior experience working in manufacturing, warehousing, or in a stockroom. The mean (SD) years of this work experience was 3.0 (4.8). Nine (16.1 %) of the 56 participants reported having some experience working with robots. This study was reviewed and approved (Protocol ID: 19-NIOSH-83) by the CDC NIOSH Institutional Review Board (IRB).[1]

2.2. Experiment setup

A projection-based VR CAVE system (MechDyne Corporation, Marshalltown, Iowa) was used to simulate working collaboratively with a robot arm. The VR CAVE consisted of three walls measuring 3.96 m (13 ft) wide and 3.05 m (10 ft) high and a floor screen measuring 3.96 m (13 ft) wide and 3.96 m (13 ft) long. The participants wore a pair of active-stereo shutter glasses making the environment look 3-Dimensional (3D). A position tracking system (Advanced Realtime Tracking (ART), Weilheim, Bayern, Germany) was used to track the participant's head, hands, and body position. Virtual images were updated in real-time to give the participants an accurate perspective. Fig. 1 displays an example of the VR CAVE environment.

The environment included three different sized digital models of robot arms from Universal Robots including the small-sized UR3 (Pay load: 3 kg, Max reach: 500 mm, Base footprint: 128 mm), medium-sized UR5 (Pay load: 5 kg, Max reach: 850 mm, Base footprint: 149 mm), and large-sized UR10 (Pay load: 12.5 kg, Max reach: 1300 mm, Base footprint: 190 mm). Each model consisted of a base, shoulder, elbow, and wrist joint. The total number of joint degrees of freedom was limited to 5, 6, or 7 based on the specific task conditions. The robot arm movement and end-effector trajectories became smoother (e.g., less rigid and robotic) with increasing degrees of freedom, enabling more flexible trajectories during the pick-and-place task.

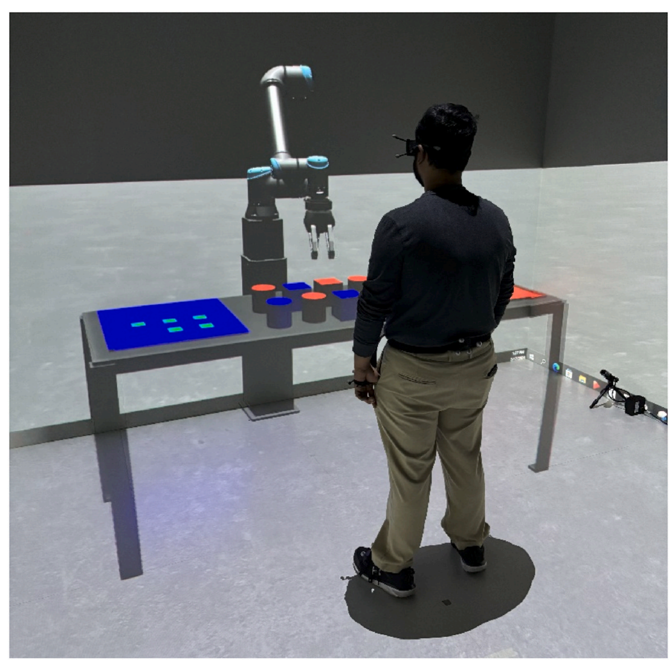

Fig. 1. Example picture of the experiment setup. The pictured robot is a simulated UR10 from Universal Robots.

[1] See 45 C.F.R. part 46; 21 C.F.R. part 56.

The Unity game engine (Unity Technologies, San Francisco, CA) was the basis of the interactive environment, which consisted of a virtual workstation table with virtual objects (e.g., cylinders and cubes) positioned in the middle and the 3D models of the robot arms. The hand trackers enabled the participants to manipulate the virtual objects on the table during the experiment task.

Fig. 2 shows a schematic of the table layout used for the pick-and-place task. Participants were instructed to stand in the center at a comfortable distance away. The height of the table was 0.91 m (3 ft). There was a total of 10 objects (5 cubes and 5 cylinders) arranged on the table. The cubes measured 100 mm^3 and the cylinders measured 100 mm in diameter and 100 mm in height. Five of the objects were red and five were blue. The objects were dispersed on 10 pre-selected locations within the workstation area to force path crossings between the participant's arm and the robot arm. The starting position for each object was randomized across trials. Due to the difference in sizes between the robot models, the layout of the objects on the table were slightly different for the UR3 compared to the UR5 and UR10 robot arm conditions. This was necessary for the robot to be mounted on the table and capable of reaching the 10 initial object positions and the five positions on the placement platform.

2.3. Experiment design and procedure

After providing informed written consent, participants answered questionnaires on demographics, prior work experience, experience working with robots, and the Negative Attitude towards Robot Scale (NARS) (Nomura et al., 2006). Experimenters then applied motion capture markers to the participant's feet, waist, and hands. Participants also wore VR glasses with motion capture makers attached to the frame. Prior to the experiment trials, participants completed a 10-min practice session to become familiar with the VR environment, practice picking up and releasing the virtual objects, and learn how to conduct the experiment task.

This study was a repeated measures experiment. We manipulated robot arm size (small, medium, and large) that was defined by the general physical characteristics of the UR3, UR5, and UR10 robots listed above, robot movement speed (60 deg/s, 120 deg/s, and 180 deg/s), and degrees of freedom (5 axes, 6 axes, and 7 axes). Each of the 27 conditions (3 sizes × 3 speeds x 3 degrees of freedom) were completed for a total of 27 experiment trials. The presentation of the conditions was randomized. The trial number for each condition was counterbalanced across participants to minimize learning effects.

For each experiment trial, participants completed a virtual pick-and-place task while standing across a table from the robot. Participants were instructed to pick up the five blue objects with their right hand and place them on a tray located on the left side of the table. Thus, within each experiment trial the participant performed five reach movement repetitions. The robot concurrently picked and placed the five red objects on a tray located on the right side of the table.

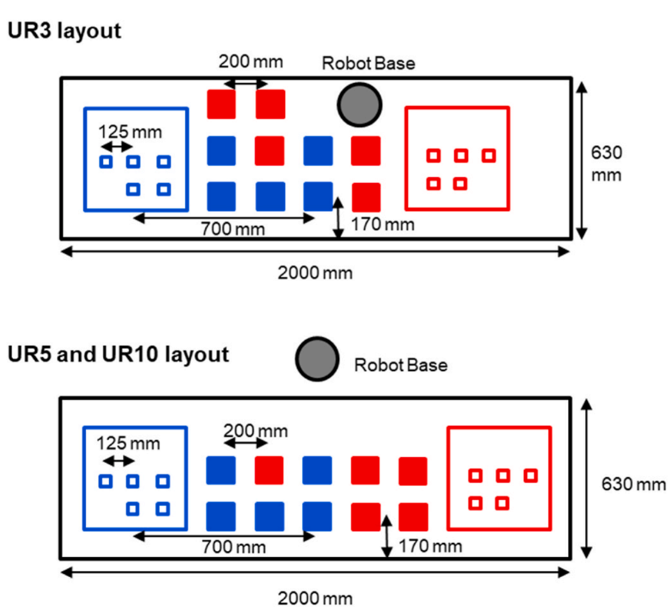

Fig. 2. Top-down view of the table layout for the UR3 robot condition (top) and the UR5/UR10 robot condition (bottom).

2.4. Independent variables

The independent variables included the robot arm size (small, medium, and large), arm speed (60 deg/s, 120 deg/s, and 180 deg/s), and degrees of freedom (DoF: 5 axes, 6 axes, and 7 axes).

2.5. Dependent variables

There were three categories of dependent variables including self-reported measures, task performance, and human motion behaviors. Self-reported measures included participant ratings for perceived safety, mental workload, and robot trust. Perceived safety was evaluated by ratings for "surprise" and "fear", on a 6-level scale with 1-"never" to 6-"very much" (Nonaka et al., 2004). Feelings of surprise and fear are key emotional drivers that influence how people perceive safety. This scale was previously used and validated in Nonaka et al. (2004). Mental workload was measured using the NASA Task Load Index (NASA-TLX) (Hart and Staveland, 1988). Robot trust was measured using ratings for 10 items adapted from a 14-item list (i.e.., function successfully, act consistently, reliable, predictable, dependable, meet the needs of the mission, have errors, provide appropriate information, unresponsive, and malfunction) on a scale from 0 to 100 % (Schaefer, 2013). Total trust score was calculated by averaging the ratings for all 10 items (Note: ratings for have errors, unresponsive, and malfunction were reversed).

Task performance measures included the total task time (i.e., duration between picking up the first object and placing down the final object) and the total idle time (i.e., duration of time spent waiting in between reach movements without an object in hand) for each separate trial.

Human motion behaviors included the average hand speed during each of the five reach movement repetitions within each respective trial. Hand speed was calculated using a motion capture marker cluster which was strapped to the back of the participant's right hand.

2.6. Statistical analysis

All statistical analyses were conducted using SPSS v29 (IBM Corporation, Armonk, NY, USA) with statistical significance achieved when $p < 0.05$. We compared the effect of participant characteristics (i.e., age, sex, years of experience, prior experience working with robots) on the NARS score using a mixed effects model. Mixed effects models were used to test for the effect of the independent variables on the dependent variables. All two-way interactions and the three-way interaction were included in the models. Covariates in the model included participant age, sex (male vs. female), trial number (1–27), years of manufacturing, warehousing or stockroom work experience, experience working with robots (yes vs. no), and the total NARS score. Bonferroni tests were used for post-hoc pairwise comparisons. All statistical results are presented as mean ± standard error (SE) in the original units.

3. Results

Table A1 in the appendix presents a summary of the p-values from the mixed effects models investigating the effect of arm size, arm speed, DoF, and all two-way and three-way interactions on the dependent variables.

3.1. Participant characteristics

Increasing age corresponded to a statistically significant increase in total task time ($p = 0.027$) and total idle time ($p = 0.029$). Participants with prior experience working with robots had statistically significantly faster hand speeds during reach movements, compared to those without experience ($p = 0.050$). Sex, years of work experience, and total NARS score did not significantly influence any of the dependent variables.

3.2. Perceived safety

Ratings for surprise and fear followed similar trends across the task conditions. Both ratings significantly decreased ($p < 0.001$) with increasing trial number. For surprise, the effects of arm speed ($p < 0.001$), the two-way interaction between arm speed and arm size ($p = 0.013$), and the three-way interaction between arm speed and arm size, and DoF ($p < 0.001$) were significant. Similarly, for fear, the effects of arm speed ($p < 0.001$), arm size, ($p = 0.023$), the two-way interaction between arm speed and arm size ($p < 0.001$), and three-way interaction between arm speed and arm size, and DoF ($p < 0.001$) were significant. For fear, the large arm size (1.44 ± 0.08) had significantly higher ratings than the small arm size (1.35 ± 0.08; $p = 0.018$), while there was no change in surprise ratings across arm sizes. For fear and surprise ratings, the three-way interaction effects between arm speed, arm size, and DoF are shown in Fig. 3. In general, both ratings followed a similar trend across the three variables, where they statistically significantly increased with faster speeds within each arm size and DoF conditions.

3.3. Trust

Trust statistically significantly increased with increasing trial number ($p < 0.001$). The main effect of arm speed ($p < 0.001$), the two-way interaction between arm size and arm speed ($p = 0.011$), and the two-way interaction between arm speed and DoF ($p = 0.031$) were significant. The trust score for the 180 deg/s arm speed (89.18 ± 1.26) was significantly lower than the trust scores for the 120 deg/s (90.31 ± 1.26; $p < 0.001$) and 60 deg/s (90.52 ± 1.26; $p < 0.001$) speeds. This trend was only found within the small and large arm sizes, as seen in Fig. 4. For the medium arm size, the trust score for the 180 deg/s arm speed (89.18 ± 1.29) was significantly lower than the trust score for the 120 deg/s arm speed (90.57 ± 1.29; $p = 0.005$) and there was no difference compared to the trust score for the 60 deg/s speed. Likewise, pairwise comparisons for the two-way interaction between arm speed and DoF indicated that the trend in trust scores across arm speeds was only prevalent in the 5 DoF condition. There was no statistically significant difference in trust score across arm speeds for the 7 DoF condition. However, the 180 deg/s arm speed (89.37 ± 1.29) was significantly lower than the trust score for the 60 deg/s arm speed (90.53 ± 1.29; $p = 0.024$) for the 6 DoF condition.

3.4. Mental workload

The NASA TLX score significantly decreased with increasing trial number ($p < 0.001$). The main effect of arm speed was significant ($p < 0.001$). Table 1 shows the comparison across arm speed conditions for the total NASA TLX score and subscales. The NASA TLX score for the 180 deg/s arm speed (47.47 ± 6.13) was significantly higher than the NASA TLX scores for the 120 deg/s (40.79 ± 6.13; $p < 0.001$) and the 60 deg/s (38.20 ± 6.13; $p < 0.001$). No other main effects or interaction effects were statistically significant for the NASA TLX score.

3.5. Task performance

Generally, the trends in the findings for total task time and idle time were similar. Total task time significantly decreased ($p < 0.001$) with increasing trial number. For both performance variables, the main effects of arm size (total task time and idle time: $p < 0.001$) and DoF (total task time: $p < 0.001$; idle time: $p = 0.010$) were significant. Total task time was significantly shorter for the small arm size (15.09 ± 0.48) compared to the medium (16.51 ± 0.48; $p < 0.001$) and large (16.17 ± 0.48; $p < 0.001$) arm sizes. Additionally, total task time was statistically significantly shorter for the 7 DoF condition (15.41 ± 0.48) compared to the 6 (16.09 ± 0.48; $p < 0.001$) and 5 (16.28 ± 0.48; $p < 0.001$) DoF conditions. Idle time was significantly shorter for the small arm size (7.57 ± 0.36) compared to the medium (8.28 ± 0.36; $p < 0.001$) and large (8.01 ± 0.26; $p = 0.006$) arm sizes. Idle time was statistically significantly shorter for the 7 DoF condition (7.71 ± 0.36) compared to the 5 DoF condition (8.14 ± 0.36; $p = 0.010$). The main effect of arm speed and the interaction effects were non-significant for total task time and idle time.

3.6. Human motion behaviors

Average hand speed significantly increased ($p < 0.001$) with increasing trial number. The main effects of arm size ($p < 0.001$) and DoF ($p = 0.002$) were significant. Hand speed was statistically significantly slower for the small arm size (0.521 ± 0.013) compared to the medium (0.577 ± 0.013; $p < 0.001$) and large (0.578 ± 0.013; $p < 0.001$) arm sizes. Additionally, hand speed was statistically significantly slower for the 5 DoF condition (0.550 ± 0.013) compared to the 6 DoF (0.564 ± 0.013; $p = 0.003$) and the 7 DoF (0.562 ± 0.013; $p = 0.016$) conditions. The main effect of arm speed and the interaction effects were non-significant.

4. Discussion

The purpose of this experiment was to investigate the effect of robot arm size, movement speed, and degrees of freedom on human behavior, task performance, perceived safety, trust, and mental workload in a collaborative pick-and-place task. In general, we found that while arm speed significantly impacted the self-reported outcomes, it did not significantly affect task performance and human behavior. Conversely, arm size and degrees of freedom had more of a statistical effect on task performance and human behavior, compared to the self-reported measures. Participant sex and relevant work experience did not impact any of the task outcomes, though increasing age led to a significant decrease in task performance. Overall, participants reported low ratings for surprise and fear, high levels of trust in the robot, and low mental workload scores, across all task conditions.

4.1. Self-reported measures

Our findings show that an increase in robot arm speed corresponded to lower perceived safety, lower trust levels, and higher mental workload ratings. All the workload subscale ratings followed the same trend across speed conditions, except ratings for frustration, which were inversely related with speed. These findings are mostly in agreement with past research investigating the effects of arm speed in HRI with a robot arm (Story et al., 2022; Tan et al., 2009). Tan et al. (2009) found a positive correlation between robot speed, mental workload, and ratings of fear and surprise. Story et al. (2022) found higher levels of workload with faster arm speeds in an object assembly task where participants worked in collaboration with a physical UR5 robot. However, trust levels remained consistently high regardless of arm speed. The differences are likely due to variations in speeds between experiments where Story et al. (2022) used 36, 48, and 60°/s compared to 60, 120, and 180°/s in the current study. In contrast to our findings, Gervasi et al. (2024) reported that movement speed had no impact on workload ratings and perceived safety, but participants perceived the robot as more helpful, efficient, fluid, and slightly more uncomfortable with an increase in movement speed during a product assembly task.

We found that fear ratings were positively related to robot arm size,

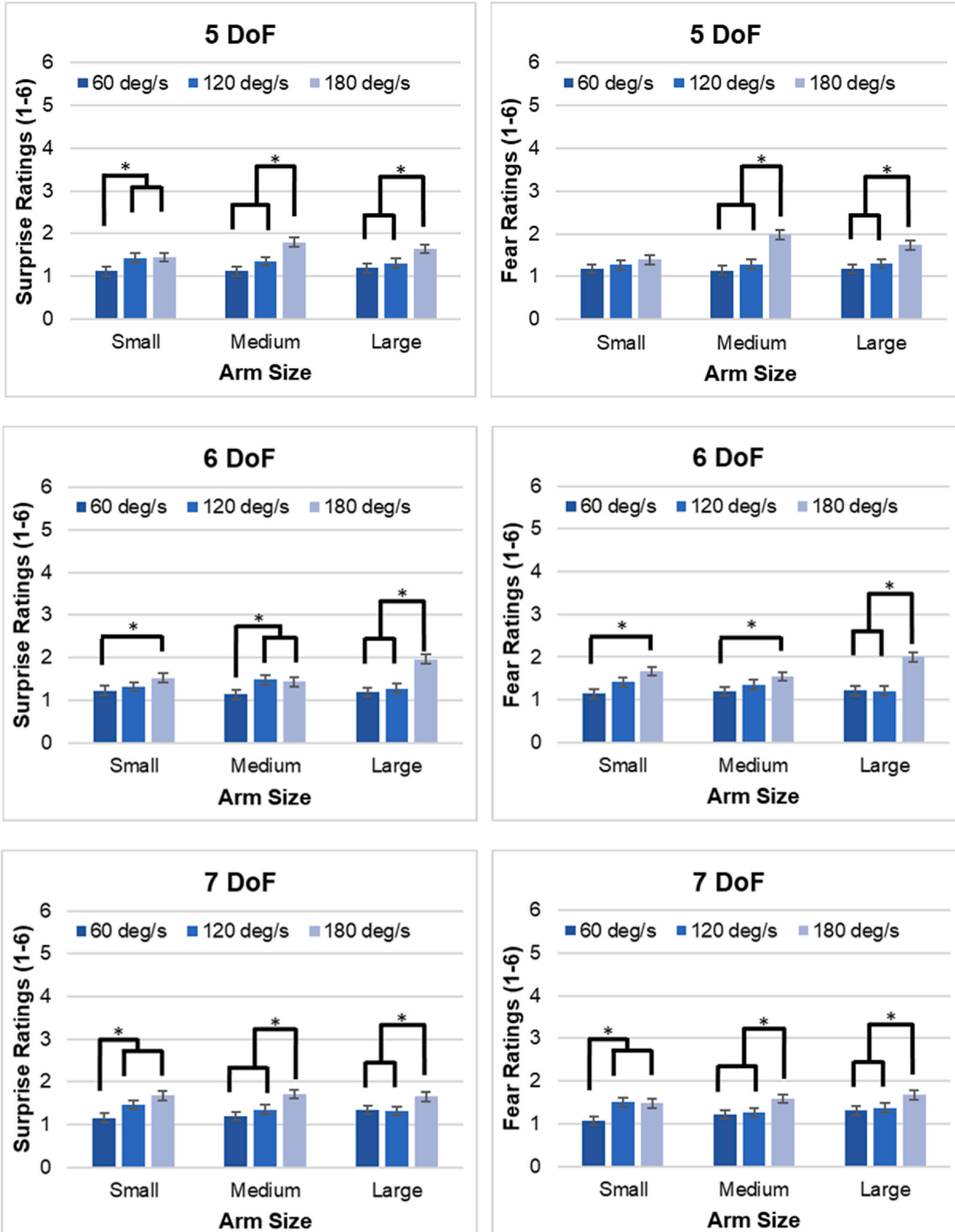

Fig. 3. Surprise (Left) and Fear (Right) ratings by arm size and arm speed for each degrees of freedom (DoF) condition. Error bars indicate standard error. An asterisk (*) indicates a significant difference between conditions.

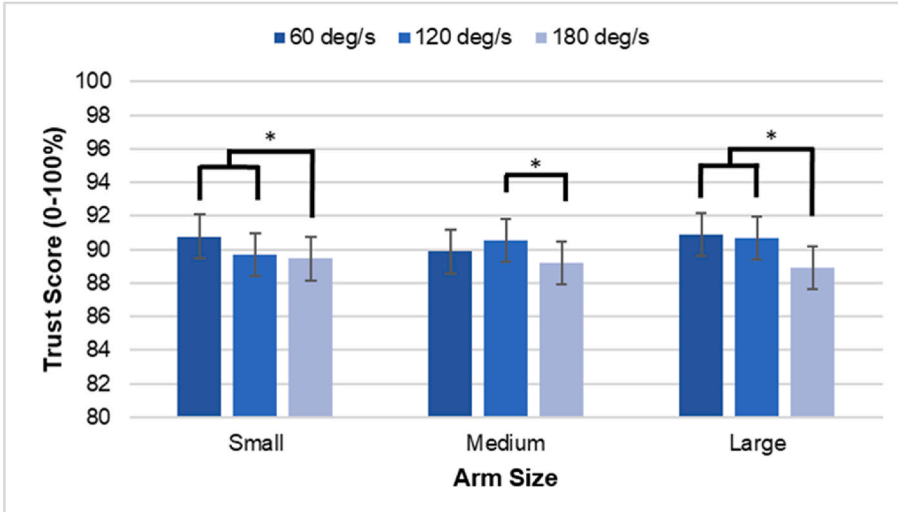

Fig. 4. Trust score by arm size and arm speed. Error bars indicate standard error. An asterisk (*) indicates a significant difference between conditions.

Table 1
The paired t-tests for the NASA TLX workload and subscale ratings. The mean difference corresponds to the subscale score for the speed condition in the (I) column minus (J) column. An asterisk (*) indicates a significant difference.

Subscale	Speed (I)	Speed (J)	Mean Difference (I – J)	Standard Error	*p*-value
Mental Demand	60	120	−0.465	0.552	1.000
		180	−1.901	0.552	0.002*
	120	180	−1.436	0.552	0.028*
Physical Demand	60	120	−0.495	0.227	0.088
		180	−0.959	0.227	<0.001*
	120	180	−0.464	0.227	0.123
Temporal Demand	60	120	−2.469	0.430	<0.001*
		180	−6.167	0.430	<0.001*
	120	180	−3.698	0.430	<0.001*
Performance	60	120	−0.406	0.224	0.210
		180	−0.742	0.224	0.003*
	120	180	−0.336	0.224	0.401
Effort	60	120	−0.852	0.249	0.002*
		180	−1.623	0.249	<0.001*
	120	180	−0.772	0.249	0.006*
Frustration	60	120	2.104	0.401	<0.001*
		180	2.126	0.401	<0.001*
	120	180	0.021	0.401	1.000
Total NASA TLX	60	120	−2.581	1.296	0.140
		180	−9.266	1.296	<0.001*
	120	180	−6.685	1.296	<0.001*

whereas size did not affect trust, mental workload, and surprise. In Gervasi et al. (2024), participants perceived the larger robot to be slightly safer, more efficient, fluid, and trustworthy, however there was no effect on mental workload. While Gervasi et al. (2024) reported that participants perceived the larger robot as more stable in its movements, it is likely that participants in the current study viewed the robot arm as stable regardless of its size. Prior research has investigated the effect of robot size on perceived safety and trust during HRI with a mobile robot (Haney and Liang, 2024). Research shows increased perceived safety (Joosse et al., 2021) and shorter stopping distances (Jost et al., 2021) when being approached by a shorter mobile robot compared to a taller one. In our study, it is possible that the simplicity of the task and the narrow range of the robot arm sizes contributed to the similarities in the self-reported measures. Alternatively, the size of a robot may have minimal effects when they are stationary in a fixed base point compared to robots that move around the user in close proximity.

The main effect of DoF was not significant for any of the self-reported outcomes, indicating that the robot's movement path was not considerably altered when it had 5 vs. 6 vs. 7 axes of rotation. These outcomes show that restricting a robot's DoF within a specific range has little impact on a person's perceived safety, trust in the robot, and mental workload.

4.2. Task performance

Interestingly, faster robot arm speeds did not hinder task performance despite leading to lower perceived safety, lower trust levels, and higher mental workload ratings. On the other hand, decreasing robot size and more axes of rotation led to shorter task and idle times. Performance efforts may have improved under these conditions if avoiding the smaller robot arm during the reach movements was easier compared to the larger robot arm size. It is well understood that occupational stressors are related to poor job performance. The relationship between task performance and perceived safety in HRI with a robot arm is often interdependent and critical to the success of collaboration in shared workspaces (De Simone et al., 2022). In our study, the simplicity of the experiment task could explain the similarities in performance across robot arm speeds. Although participants reported statistically significantly lower perceived safety, lower trust levels, and higher mental workload for faster robot arm speeds, the practical significance of these differences is not enough to impede performance.

4.3. Human behavior

Like the trend in task performance, robot speed did not significantly affect participant hand speed during the experiment task. This result differs from the previous finding, demonstrating that faster robot speeds lead to lower human walking speeds when interacting with a mobile robot (Chen et al., 2018). Interestingly, increasing robot size and decreasing DoF resulted in faster hand speeds in our study. Human behavior metrics are commonly employed in HRI research to provide insight into perceived safety and trust during interaction with a robot (Hopko et al., 2022). Hand speed and motion have not been studied in relation to perceived safety and trust during HRI with a robot arm. In the case of our experiment, considering that robot size and DoF had limited impact on the self-reported measures, it is likely that hand speed variation across these conditions is unrelated to perceived safety and trust and that it is rather a result of the task design. For example, it could be that participants were required to make quicker reach movements to avoid collisions with the larger robot arms and movement paths that had fewer DoF. Nevertheless, more research is needed to form any conclusions.

Some other alternative and supplemental human behavior metrics that were not included in this study but are common in HRI research include physiological signals (e.g., heart rate, electrodermal activity, and electroencephalogram) and eye tracking data (Hopko et al., 2022). Physiological signals can provide valuable insight to how people's perceptions change over time; however, some findings suggest that there is little variation in physiological signals during HRI or that the changes are very subtle (Gervasi et al., 2024; Weistroffer et al., 2013). For example, Gervasi et al. (2024) found no change in heart rate variability and electrodermal activity across robot size and speed conditions in a collaborative assembly task. Additionally, eye-tracking provides detailed insights into human attention, perception, and cognitive load during interactions with robots. For instance, it can be used to evaluate human trust in a robot by observing how closely a person monitors the robot's actions.

4.4. Implications for design

The findings from this research can provide information for robot manufacturers, safety professionals, and workplace designers. Although current standards for the safe implementation of robots in collaborative environments define speed and proximity limits in relation to physical safety when operating in the presence of human coworkers, human perception of safety was not considered. These results indicate that considering the incorporation of human perception of safety during the design and movement characteristics of robots may support their acceptance in the workplace. Research in this area is somewhat limited as robots in collaborative environments are an emerging technology. Our findings show that robot arm speed has a larger impact on perceived safety, trust, and mental workload compared to robot arm size and DoF, while it had a non-significant effect on task performance, and human behavior. Thus, specifically in collaborative applications with robot arms, it would be beneficial for the well-being of workers to opt for slower movement speeds if productivity allows for it. Prolonged interaction with robots introducing negative experiences could increase worker stress and fatigue/emotional exhaustion. However, it is important to note that, although we found statistically significant differences, participants overall reported high levels of perceived safety, high levels of trust in the robot, and low mental workload scores across all task conditions. The robot arm speeds in this study were above the maximum limit defined by the current robot standards, which indicates that people felt safe and trusted the robot.

4.5. Limitations

This research has a few limitations. The task did not require physical interaction with the robot arm. A more complex task, like a handover or product assembly task, could impact the findings. Additionally, participants were aware that the virtual robot was incapable of colliding with them or causing physical harm. This could have impacted responses to the self-reported measures. Task performance measures were limited to total task time and the total idle time due to the capabilities of the VR environment. Measurement of operator error and collisions with the robot could have potentially provided more insightful findings. The evaluations for perceived safety, trust in the robot, and mental workload were based only on subjective questionnaires that may not accurately reflect an individual's psychophysiological state. This approach lacks objectivity, and responses could be susceptible to internal or external biases leading participants to overestimate or underestimate their perceptions. Data collection methods would have benefited from the addition of physiological (e.g., heart rate and EEG) and eye tracking measurements to corroborate the self-reported measures of safety and trust and to garner more objective levels of stress during the experiment.

4.6. Conclusions

In summary, this study indicates that the design and movement characteristics of robots in collaborative environments may influence human perceptions and behavior in a shared work environment, particularly regarding perceived safety, trust, and mental workload during a pick-and-place task. While robot arm speed had a statistically significant impact on self-reported measures, it had a non-significant effect on actual task performance and human behavior. Conversely, the size of the robot arm and its degrees of freedom had a greater influence on task performance and human behavior than on the self-reported outcomes. These findings may provide insights for robot manufacturers and standard committees when considering how to improve perceived safety in the workplace. Future research could investigate HRI in more complex and realistic work scenarios, as well as the effect of different robot characteristics, such as the type of robot end-effector. Additionally, future work could include the analysis of eye-tracking data and changes in human physiology to provide a more holistic understanding of the comparison between perceived and physical safety during HRI.

CRediT authorship contribution statement

Justin M. Haney: Writing – original draft, Project administration, Investigation, Formal analysis, Conceptualization. **Douglas Ammons:** Investigation. **HeeSun Choi:** Writing – review & editing, Writing – original draft.

Disclaimer

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Results from the mixed effects models investigating the effect of arm size, arm speed, degrees of freedom (DoF), and all two-way and three-way interactions on all the dependent variables. The values in each cell represent the corresponding *p*-values with a *p*-value <0.05 indicating a significant effect denoted by an asterisk (*)

Dependent Variable	Arm Size	Arm Speed	DoF	Arm Size * Arm Speed	Arm Size * DoF	Arm Speed * DoF	Arm Size * Arm Speed * DoF
Task Performance							
Participant Time	<0.001*	0.768	<0.001*	0.952	0.588	0.533	0.626
Total Idle Time	<0.001*	0.819	0.01*	0.753	0.472	0.329	0.457
Human Behavior							
Total Average Speed	<0.001*	0.798	0.002*	0.479	0.902	0.457	0.667
Perceived Safety							
Surprise	0.283	<0.001*	0.367	0.013*	0.343	0.975	<0.001*
Fear	0.023*	<0.001*	0.611	<0.001*	0.067	0.082	<0.001*
Trust							
Function Successfully	0.164	0.001*	0.661	0.231	0.838	0.188	0.157
Act Consistently	0.522	<0.001*	0.729	0.024*	0.407	0.109	0.120
Reliable	0.383	<0.001*	0.129	0.150	0.720	0.032*	0.224
Predictable	0.855	<0.001*	0.353	0.010*	0.138	0.336	0.375
Dependable	0.721	0.002*	0.129	0.062	0.445	0.030*	0.011*
Perform as Instructed	0.210	0.094	0.267	0.065	0.647	0.030*	0.357
Have Errors Reversed	0.485	<0.001*	0.763	0.563	0.663	0.296	0.746
Provide Appropriate Info	0.418	0.319	0.409	0.075	0.220	0.299	0.914
Unresponsive Reversed	0.051	0.001*	0.843	0.800	0.295	0.711	0.703
Malfunction Reversed	0.858	<0.001*	0.585	0.531	0.799	0.058	0.562
Trust Total	0.472	<0.001*	0.679	0.011*	0.576	0.031*	0.222
Mental Workload							
Mental Demand	0.514	0.002*	0.169	0.254	0.518	0.502	0.383
Physical Demand	0.804	<0.001*	0.239	0.832	0.187	0.796	0.996
Temporal Demand	0.586	<0.001*	0.107	0.730	0.481	0.728	0.145
Performance	0.888	0.004*	0.114	0.095	0.423	0.470	0.087
Effort	0.489	<0.001*	0.023*	0.661	0.819	0.537	0.569
Frustration	0.012*	<0.001*	0.846	0.092	0.222	0.056	0.090
NASA TLX Total	0.966	<0.001*	0.063	0.440	0.227	0.192	0.350

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