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A Video-Based Crowdsourcing Study on User Perceptions of Physically Assistive Robots

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Abstract

Physically assistive robots (PARs) support people with disabilities in performing daily tasks, yet there is limited research on how PAR movements (e.g., speed) affect user attitudes and emotions (e.g., discomfort, robot's competence). Since lab-based studies are limited in scalability and diversity of participants, we explored video-based crowdsourcing as a method to collect user perceptions in three caregiving tasks with a robotic arm (forearm cleaning, blanket manipulation, and dressing). In study 1, 16 participants assessed how well different video angles and sound conditions simulated in-person interactions. The results showed high similarity ratings between videos and real experience. In study 2, 110 online participants rated the robot's social attributes and their own emotional responses while observing a person experiencing those tasks in videos. Our results show that user ratings are influenced by the task, PAR motions, and users' general attitudes and highlight the potential of crowdsourcing as a method for studying PARs.

CCS Concepts

• **Human-centered computing** → *User studies.*

Keywords

Physically Assistive Robots, Physical Human-Robot Interaction, User Perception, Crowdsourcing, Online Study

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1 Introduction

Physically assistive robots (PARs) can improve accessibility and independence for individuals with disabilities in performing daily tasks. As PARs continue to develop, they are expected to assist in increasingly complex tasks, including dressing, bathing, object handling, eating, mobility assistance, limb replacement, limb rehabilitation, and body augmentation [39]. During these tasks, PARs contact the user's body or manipulate objects in close proximity to users. Thus, while technical advancements are critical, considering user attitudes and emotions towards the social attributes of robots, is also important for successful human-robot interaction (HRI) and user adoption. Such perceptions focus on topics like anthropomorphism, likeability, warmth, competence, discomfort, etc., which can determine how the perceived attributes affect the quality of interaction with robots [7, 14].

Prior research has shown that robot movements, such as retraction speed in human-to-robot handover [43] or the direction of a robot's approach [63], can influence user perceptions, there is limited work on user perception of PARs and how their movement (e.g., speed) in the personal space around the user's body can affect user perceptions during assistive tasks. Moreover, gathering sufficient data on a large number of movement-related factors in laboratory settings is challenging. The limited diversity of in-lab participants further reduces the generalizability of in-lab findings. Previous HRI research suggests that online video-based experiments can inform the design of robots' appearance and direction of approach [4, 63]. While direct contact cannot be replicated in online studies, neuroscientific research suggests that simply observing actions can activate premotor neurons in the brain, leading to vicarious experience of actions, sensations, and emotions [5, 29, 50]. This literature suggests that, if designed well, videos can help collect large data on user perceptions of PARs.

In this work, we assessed user perceptions of PAR movements with diverse participants through video-based crowdsourcing. We designed three caregiving tasks (forearm cleaning, blanket manipulation, and dressing) using a Kinova Gen3 [32] robotic arm and ran two studies. In Study 1, lab participants rated how well different video angles and soundtracks simulated real physical experiences. All videos received high similarity scores (over 7 on a 1 to 9 scale) suggesting the efficacy of videos but participants overall preferred the first-person view with the robot's movement sound. In Study 2, 110 online participants watched first-person videos of a person interacting with the robot under varing robot's *movement speed* and a task-specific *distance* variable: the cleaning range for forearm cleaning, lifting distance for blanket manipulation, and gripper-to-arm distance for dressing, then completed the Robotic Social Attributes Scale (RoSAS) [14] and the Valence, Arousal, and Dominance (VAD) [12] questionnaires. Results showed that people's perceptions depend on the task being performed, the proximity of the robot to sensitive areas of the body, and the nature of the robot's movements. Also, their pre-established attitudes toward robots impacted ratings on social attributes and emotional responses. Our

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contributions are (1) An exploration of how different video presentation methods influence participants' perceived similarity between videos and actual experiences; (2) Findings on how robot movements and user background impact user emotions and the perceived social attributes of a PAR in three assistive tasks from a crowdsourcing study.

2 Related Work

User Perception of Physically Assistive Robot. The past decade has seen a drastic increase in research on physically assistive robots [39] and tasks such as navigation [15, 52, 66], feeding [8], and delivering medication to patients [46]. In contrast, there has been relatively little research in understanding users' emotions and perceptions toward the PAR. Research shows that users form a perception of robots based on interaction parameters (e.g., duration, location, speed) of the robot [55]. For example, one study evaluated the social perception of human-robot handovers by examining user attitudes towards various reaction speeds, arm positions, and grasp types [43], while another showed that parameters such as pressure and duration impact users' comfort levels in robot hug [11]. While these studies on humanoid and industrial robots provide valuable insights into the design of robots for specific HRI tasks, PARs fundamentally differ from these robots because they maintain a more enduring and intimate interaction space with humans. Our work provides data on how PAR movements influence users' perceptions and emotions.

Online Studies of Human-Robot Interaction. Online HRI experiments have expanded significantly [2, 4, 26, 27, 45, 56], examining factors such as trust, fear, and robot characteristics like humanness and uncanniness [1, 4, 45, 56], as well as persuasiveness, trust, and reliability [31], and the dynamics of robot-human approach direction [63].

Similarly, some physical HRI (pHRI) researchers have used video-based studies. Willemse et al. [61] gathered online data on the pleasantness of stroking touches, confirming prior in-lab findings and revealing interactions between stimuli types and stroking velocity. Law et al. [34] explored the impact of a robot's touch on trust, helping to narrow conditions for future lab studies. Others used videos to investigate the interplay between robot touch and factors like proactivity, social appearance, and error presence on user perceptions [17, 18]. We investigate whether video-based crowdsourcing can offer insights into more complex assistive tasks involving sustained physical contact with a robot.

A significant challenge in online studies of pHRI is designing videos that effectively simulate the experience of direct interaction with robots. Researchers have adopted varied video designs for their studies. For instance, Willemse et al. [61] utilized first-person view to capture the stroking interactions, while others employed third-person long-shots to capture human-robot touch [17, 18, 34]. Kunold et al. [33] used third-person long-shot videos and found no evidence that video-based studies elicit the same emotional or behavioral responses as live interactions. Thus, little is known about how effective different video angles are in conveying pHRI. Past research showed that sounds made by robots influence human perceptions during interactions [65], particularly affecting perceived movement quality, while having less impact on functional aspects like safety and capability [51]. Lohse et al. [35] found that participants preferred a robot's sound to be congruent with its movements. Our work explored various video angles and the presence or absence of robot noises to determine which combination best replicates the real in-lab experience for online observers.

Neuroscientific Insights: Mirror Neurons and Empathy. Whenever we see what happens to others, we not only understand what they experience but also often empathically share their states. In the nineties, a series of experiments showed that some premotor neurons, called mirror neurons, fired during both action execution and the observation of the same action [49]. Recent neuroscientific findings suggested that observing others being touched on hands [20], legs[30], neck, or face[10] can trigger activity in certain brain regions that are also responsive when we are touched on the same body part [29]. This vicarious effect is likely the result of the human ability to empathize with others cognitive and emotional states [28, 60]. It is supported by the fact that vicarious experience of both pleasant and unpleasant somatosensory stimuli has been shown to activate regions of the cortex associated with imitation and socio-emotional behavior [13, 23, 38]. Neuroscience studies often assess empathy using Empathy Quotient (EQ) [6] and Interpersonal Reactivity Index (IRI) [19]. Research has shown that higher scores on IRI subscales are linked to higher levels of vicarious activation [5, 22, 44, 53, 54]. Our work builds on evidence that observing another person being touched activates neural circuits similar to those involved in actual touch. We collect participants' IRI scores to assess their empathy levels in our crowdsourcing study.

3 Experimental Set-up and Physically Assistive Tasks

We used the Kinova Gen3 robotic arm (7-DOF) with a Robotiq 2F-85 gripper and integrated vision (Omnivision OV5640 color sensor, Intel RealSense D410 stereo depth sensor) for three assistive tasks. All communication ran through ROS. For each task, we selected two values for each of the motion-related variables (Figure 1), informed by literature, pilot testing, and the varying sensitivity of different body areas. Research suggests that tactile sensitivity varies across the body, with the forehead being the most sensitive, followed by the arm, while the legs exhibit the lowest sensitivity [3]. Because our tasks involve different contact locations —the forearm for cleaning, the legs for blanket manipulation, and the arm, shoulder, and head for dressing— these differences in sensitivity may influence participants' perceptions of the robot's touch. By considering these variations, we aimed to capture a range of physical interactions that reflect real-world assistive scenarios.

Forearm Cleaning. The robot uses a damp sponge attached to a cube to remove a washable blue marker from the participant's forearm by moving back and forth. The first variable, Cartesian velocity, has two speeds: 3 cm/s (reported as the most pleasant for stroking touch [36, 61]) and 30 cm/s (noticeably different and outside the pleasant range [9, 36]). The second variable is cleaning distance, with two stroke lengths: 6 cm and 12 cm.

Blanket Manipulation. The participant sits in a chair with their feet on a footrest, covered by a blanket. The gripper grasps the edge of the blanket from a specified location to uncover the legs.

(a) Task 1: forearm cleaning (b) Task 2: blanket manipulation (c) Task 3: dressing

Figure 1: Setups for the three assistive tasks.

Movement speeds are 3 cm/s and 30 cm/s, similar to the previous task. The second variable is blanket lifting height, set at either 10 cm or 40 cm above the body.

Dressing. The experimenter places two red stickers on the participant's arm at the elbow and shoulder, and with the arm held horizontally, the gripper moves a cloth along the arm and releases it at the marked endpoint. The speed variables remain unchanged. The second variable is the distance between the gripper and the skin. Using a sleeve with a large hole, positioning the fist at the upper edge provides about 2 cm of distance (with friction felt on the upper arm), while the lower edge creates about 8 cm of distance (with friction on the opposite surface).

4 Study I: Evaluating Video Angles and Soundtracks for Simulating PAR Experiences

The lab study used videos with varying camera angles and soundtracks to assess which felt most similar to reality.

4.1 Methods

Video Conditions. We filmed the videos with three iPhones (recording at 30 fps, 1080p) capturing simultaneously from three angles (Figure 2): a first-person view simulating the participant's perspective; a third-person long-shot view capturing both the participant and the robot and a comprehensive view of the interaction and the surroundings, and a third-person close-up view of the robot arm's contact with the participant. A fourth video combined all three views into one frame. We also used two soundtracks: one with the original robot movement noises and another muted. For the combination video, we used the audio from the first-person view. This resulted in 8 video combinations for each trial.

Procedure. We began the user study with a background questionnaire. Since this study was focused on assessing different video conditions, we did not include all four variations of robot motion for each task. Instead, we used the lower speed and shorter distance combination for all three tasks. During the main session, the participant experienced the three assistive tasks with the robot arm in a randomized sequence. After experiencing each task, the participant watched the eight video combinations in a random sequence and rated how *similar* the videos felt to the in-person experience with the robot on a scale of 1 (totally different) to 9 (the same). We conducted a brief interview at the end to identify the factors that influenced participants' ratings.

Participants. We recruited 16 participants (11 male, 5 female). The participants had a mean age of 24.9 years (ranging from 23 to 29). Among them, 6 had prior experience in robotics, 2 were novices who had seen some commercial robots, 1 beginner who had interacted with commercial robots, 2 were intermediates who had designed, built, or programmed robots, and 1 was an expert who frequently designed or programmed robots. The participants received $15 for a 75-minute study.

4.2 Results of Video Proxy Study

The average ratings for all video combinations ranged from 7-9 (out of 9), suggesting that all video conditions felt highly similar to the actual experience. Videos with sound are consistently rated higher than muted ones across all scenarios.

All similarity ratings violated the assumption of normality. Thus, we applied the aligned rank transform (ART) for non-parametric factorial ANOVA [62] on the data. The Task factor had a statistically significant effect on the similarity ratings of videos to the real robot experience with a small to medium effect size ($F(1, 15)$=4.7192, p=.0095, η_p^2=.03). Post hoc pairwise comparisons using ART-C [21] revealed that task 1 (M=7.94, SD=1.45) was rated significantly higher than task 3 (M=7.4, SD=1.77) with a p-value of .0078, while no significant differences were found between task 1 and task 2 (M=7.81, SD=1.39) or between task 2 and task 3. Additionally, no other main effects or interaction effects were observed.

In post-study interviews, participants expressed varied preferences for audio and video angles. Most (n=12) preferred sound, while some (n=3) preferred muted audio, and one had no preference. For video angles, eight favored the first-person view, while other liked the long-shot (n=3), a combination of views (n=2), or close-up shot (n=1). One expressed a preference for both long and close-up views, and another mentioned different tasks might require different views.

Quantitative analysis showed no significant preference for shooting angles or soundtracks, but qualitative differences emerged. Since the videos had similarly high ratings, we selected the first-person view with the original soundtrack based on the qualitative data for the online crowdsourcing study.

5 Study II: Evaluating User Perceptions of PAR Movements Through Crowdsourcing

We conducted an online, video-based study to gather large scale data on user perceptions of the PAR's social attributes and emotions when performing the assistive tasks with different speeds and distances.

5.1 Methods

Participants. We used Prolific [47] crowdsourcing platform to recruit 110 new participants (55 male, 55 female). We limited the participation requirement for recruiting quality participants with more than 1000 tasks with a success rate of 98% or greater. The participants had a mean age of 40.6 years (ranging from 21 to 71) and all were based in the US. Among them, 12 participants had prior experience in robotics, including 1 novice, 6 beginners, and 5 intermediates. Participants were compensated $6 upon completing the 45-minute study and passing the attention checks.

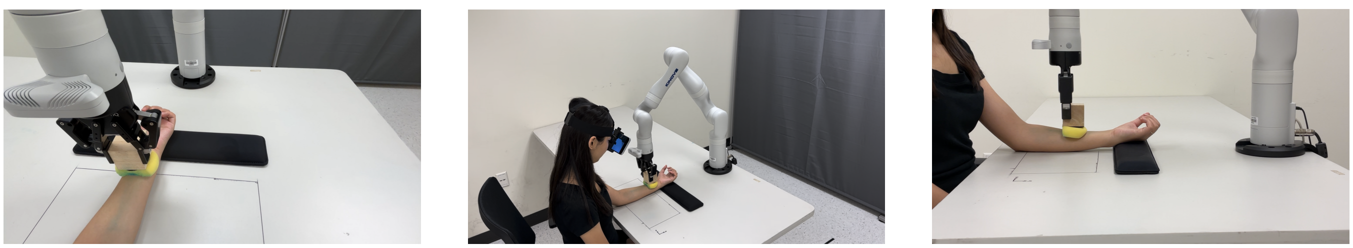
Procedure. The study began with a background questionnaire. All participants completed the Negative Attitudes Toward Robots (NARS) [40] and the IRI questionnaires to assess their attitudes toward robots and empathy. They then watched videos of three assistive tasks in random order, with four video variations per task (2 speeds $\times$ 2 distances) shown randomly. After watching each video, participants completed the RoSAS and VAD questionnaires.

5.2 Results of Online Crowdsourcing Study

Figure 3 shows the average ratings for the tasks and motion conditions. Overall, competence, user valence, and dominance were moderate, while discomfort, warmth, and arousal remained moderate to low in all conditions.

Correlation of User Ratings. Pearson correlation across user ratings for the tasks and motion parameters showed a moderate positive correlation between valence and competence (r=0.64, p<.001), suggesting higher competence ratings are linked with more pleasant feelings. Also, valence exhibited a moderate negative correlation with discomfort (r=-0.54, p<.001), indicating that more pleasant emotional responses were linked with lower discomfort with the robot. All other correlations were small or negligible. Thus, we analyzed each rating separately below.

Impact of Motion Parameters on User Ratings. We ran two-way repeated measures ANOVAs (Table 1) to examine how speed and distance affected RoSAS and emotion ratings for each task. The six ratings were treated as interval variables, and the assumptions of sphericity and normal distribution were satisfied. For task 1, speed, cleaning distance and their interaction, significantly influenced ratings of competence, warmth, and discomfort. Overall, participants rated the robot as more competent at the lower (M=4.52, SD=2.11) than the higher speed (M=4.24, SD=2.04), and the longer (M=4.57, SD=2.11) than the shorter distance (M=4.19, SD=2.04), with the effect being more pronounced at higher speed.



(a) First-person view (b) Third-person long-shot view (c) Third-person close-up view

Figure 2: Three different video angles for the forearm cleaning task.

Figure 3: Participants' ratings of RoSAS and VAD across different speed and distance conditions for the three tasks. For the X–axis labels, 'S' represents Speed and 'D' represents Distance. For example, 'S3_D6' indicates a speed of 3 cm/s and a distance of 6 cm.

Participants also perceived the robot as warmer but also more discomforting at the lower (warmth:*M*=1.94, *SD*=1.43, discomfort: *M*=2.96, *SD*=2.02) than the higher speed (warmth: *M*=1.65, *SD*=1.17, discomfort: *M*=2.53, *SD*=1.74) and the shorter (warmth: *M*=1.86, *SD*=1.38, discomfort: *M*=3.11, *SD*=2.07) than the longer distance (warmth: *M*=1.72, *SD*=1.23, discomfort: *M*=2.38, *SD*=1.69), with the effect of distance on warmth and discomfort being more pronounced at the lower speed. Valence ratings showed a significant main effect of distance and interaction effect, with participants feeling happier at the longer (*M*=5.52, *SD*=1.70) than the shorter distance (*M*=4.96, *SD*=1.73). The effect was more pronounced at the higher speed. Speed had a significant effect on arousal, with participants feeling more excited at the higher (*M*=4.00, *SD*=2.10) than the lower speed (*M*=3.74, *SD*=2.11). Distance significantly impacted dominance, with participants feeling more in control at the longer distance (*M*=5.48, *SD*=2.20) than the shorter (*M*=5.26, *SD*=2.22).

For task 2, the blanket lifting distance significantly affected participants' ratings across all six measures with medium to large effect sizes. Participants perceived the robot as more competent, less discomforting, and warmer at a shorter (competence: *M*=5.43, *SD*=2.28, discomfort: *M*=2.46, *SD*=1.76, warmth: *M*=1.68, *SD*=1.21) than a longer distance (competence: *M*=5.02, *SD*=2.36, discomfort: *M*=2.85, *SD*=1.94, warmth: *M*=1.57, *SD*=1.07). They also felt happier, calmer, and more in control in the shorter (valence: *M*=5.28, *SD*=1.58, arousal: *M*=3.63, *SD*=2.08, dominance: *M*=5.43, *SD*=2.28) than the longer distance (valence: *M*=4.87, *SD*=1.73, arousal: *M*=3.86, *SD*=2.01, dominance: *M*=5.02, *SD*=2.36).

For task 3, speed, distance (between the gripper and the forearm), and their interaction had significant effects on competence ratings. Participants perceived the robot as more competent at a lower (*M*=4.34, *SD*=2.03) than the higher speed (*M*=4.03, *SD*=2.01), and a shorter (*M*=4.31, *SD*=2.07) than the longer distance (*M*=4.06, *SD*=1.97), with the impact of distance being more pronounced at the lower speed. For warmth and valence, speed showed a significant effect. Participants reported higher warmth and happiness at a lower (warmth: *M*=1.71, *SD*=1.30, valence: *M*=5.21, *SD*=1.67) than a higher speed (warmth: *M*=1.62, *SD*=1.15, valence: *M*=4.97, *SD*=1.70). Discomfort, arousal, or dominance ratings were not significantly affected by the motion parameters.

Influence of Participant Background. Regression results on how participants' background influence each rating for each task showed that NARS-S2 (negative attitudes toward the social influence of robots) significantly affected the dominance rating in all three tasks, with p-values of .0016, .0005, and .0014, respectively. Higher NARS-S2 score was associated with lower dominance rating, suggesting that participants with more negative attitudes likely felt having less control on the robot. NARS-S1 (negative attitudes toward situations of interaction with robots) significantly affected the discomfort rating for tasks 1 and 3, with p-values of .0192 and .0392, respectively. Higher NARS-S1 scores were linked to higher discomfort ratings. Other individual-level variables (gender, age, IRI) did not significantly affect the ratings.

6 Discussion

Implications of Movement Parameters on User Perceptions of the Robot. For the forearm cleaning task, all six dimensions were significantly influenced by the robot motion. Among the three tasks, this one was closest to a touching or stroking scenario. Participants rated the robot as more competent and warmer at a lower speed, which aligns with research on social touch indicating that stroking speed follows an inverted U-curve, with the most pleasant sensation occurring between 3-10 cm/s and lower pleasantness at 30 cm/s [9, 36, 61]. Also, participants were more excited at higher speeds and felt more discomfort and less happy and in control at a shorter cleaning distance. This may be because higher speeds create more intense stimulation due to quick friction along the arm, while a shorter cleaning range may be perceived as less thorough, showing less care from the robot.

For the blanket manipulation task, participants strongly preferred a shorter blanket lifting distance across all six dimensions, likely because the robot primarily interacted with the feet and legs, which are less sensitive body parts vs. the upper body or head, making the lifting distance more important than the speed. People

Factors	Competence			Warmth			Discomfort			Valence			Arousal			Dominance		
	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
S	**11.03**	**.001**	**.092**	**27.17**	**<.001**	**.200**	**18.55**	**<.001**	**.145**	.90	.345	.008	**4.81**	**.030**	**.042**	1.81	.182	.016
D	**21.98**	**<.001**	**.168**	**5.85**	**.017**	**.051**	**66.42**	**<.001**	**.379**	**39.84**	**<.001**	**.268**	.44	.508	.004	**5.67**	**.019**	**.049**
S:D	**36.32**	**<.001**	**.250**	**21.40**	**<.001**	**.164**	**29.98**	**<.001**	**.216**	**4.79**	**.031**	**.042**	.77	.381	.007	3.07	.082	.027

(a) Task 1 - Forearm Cleaning

Factors	Competence			Warmth			Discomfort			Valence			Arousal			Dominance		
	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
S	2.43	.122	.022	.10	.758	.001	.29	.589	.003	.40	.531	.004	.002	.966	.000	.08	.782	.001
D	**11.41**	**.001**	**.095**	**7.77**	**.006**	**.067**	**18.82**	**<.001**	**.147**	**18.60**	**<.001**	**.146**	**5.06**	**.027**	**.044**	**17.70**	**<.001**	**.140**
S:D	.61	.435	.006	2.37	.127	.021	.06	.802	.001	.30	.588	.003	.91	.343	.008	.14	.706	.001

(b) Task 2 - Blanket Manipulation

Factors	Competence			Warmth			Discomfort			Valence			Arousal			Dominance		
	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
S	**13.92**	**<.001**	**.113**	**6.58**	**.012**	**.057**	.80	.374	.007	**6.15**	**.015**	**.053**	.41	.528	.009	2.90	.092	.026
D	**13.18**	**<.001**	**.108**	2.96	.088	.026	3.49	.064	.031	1.05	.307	.010	3.32	.075	.066	2.35	.128	.021
S:D	**5.16**	**.025**	**.045**	.58	.447	.005	.63	.428	.006	.43	.514	.004	.24	.629	.005	.11	.744	.001

(c) Task 3 - Dressing

Table 1: Results of two-way repeated measures ANOVAs for the six ratings across three tasks. 'Factors' refers to the within-subject factors: 'S' for Speed, 'D' for Distance, and 'S:D' for their interaction. F **represents** $F(1, 109)$ **in all cases.**

also tend to lift blankets only slightly to uncover themselves, reinforcing this preference. For the dressing task, participants rated the robot as more competent, warmer, and felt happier when the robot operated at a lower speed, likely due to its proximity to the head. They also perceived the robot as more competent when the gripper was closer to the upper surface of the forearm, likely because there was less friction and fewer tugs at the elbow, enabling a smoother and more functional movement.

A key distinction of PAR settings is their interaction with body areas of varying tactile sensitivity, which plays a crucial role in shaping user perceptions. Our results suggest that sensitivity differences across the body may contribute to how participants experience robot interactions. The forearm, a relatively sensitive area rich in mechanoreceptors, responded strongly to speed variations, aligning with prior findings on social touch. In contrast, interactions with the feet and legs during blanket manipulation were influenced more by movement range than speed, consistent with these areas' lower tactile acuity. Notably, the dressing task, which involved proximity to the head, a highly sensitive and socially intimate body part, elicited strong preferences for slower speeds. These findings highlight the importance of designing PAR movements that consider bodily sensitivity variations to enhance both physical comfort and social acceptability. Beyond PARs, our insights can inform broader applications. For instance, human-robot interactions involving the arm in PAR settings could provide valuable guidance for cobot interaction in industrial environments, where robots frequently collaborate with humans and physical contact is common [16].

Our results provide insights for researchers developing algorithms for PARs [37, 48] and pHRI [24, 25, 55]. These algorithms can adapt to varying speed and distance parameters depending on different conditions. Nummenmaa et al.[42] developed bodily maps of emotions, visually representing areas of the body where individuals experience increased or decreased sensations in response to various emotions. Similarly, Suvilehto et al.[57] created Touchability Maps, relationship-specific body maps indicating where people allow others to touch them based on emotional closeness. Future work could explore developing a body map that goes beyond social touch, focusing on how different movement parameters, such as speed and proximity, influence people's feelings of discomfort, fear, and other emotional responses during physical interactions. This map would help identify thresholds for acceptable robot movements in relation to various body parts, contributing to more adaptable and user-friendly PARs.

Participants' Background Affects the Perceptions toward the PAR.

Our results indicated that NARS scores influenced user ratings. Participants with higher negative attitudes toward the social influence of robots (NARS-S2) scores felt less dominant (in control) across tasks, aligning with findings that perceiving robots as more autonomous can reduce users' sense of control [41, 67]. Those with more negative attitudes toward robot interaction (NARS-S1) reported significantly more discomfort in the cleaning and dressing tasks, likely due to the close proximity and direct physical contact involved, echoing earlier results [58]. Thus, NARS scores appear predictive of pHRI perceptions and should be collected in PAR studies. In contrast, gender, age, and user empathy had no effect on user ratings, suggesting they may be less relevant to control in online PAR studies.

Limitations and Ongoing Work. Our work has several limitations which provide avenues for future work. First, we acknowledge that in Study 1, participants experienced both the experiment and video review in close succession, which may have led their immediate recollections to influence their video-based evaluations. Second, we acknowledge that online videos cannot fully capture the tactile nuances of real physical interactions, so online ratings may differ from in-person experiences. Specifically, a study by Tsoi et al. [59] suggested a significant difference in robot perceptions between the real and the simulated environment. Thus, future research can conduct Study 2 in the lab to investigate any mismatches with our results and evaluate the limitations of crowdsourcing for PAR research. Still, online studies can narrow down the conditions that must be tested for laboratory studies, allowing future in-lab studies to focus on the most critical variables requiring direct physical interaction, making these experiments more feasible and targeted. Future work could explore the integration of virtual reality (VR) or commercial haptic devices to better replicate physical interactions and provide a more immersive and tactile experience in online environments [64] as VR offers richer spatial perception (e.g., environmental cues and depth) than 2D videos, while wearable haptics enable remote participants to physically sense the robot's contact. Third, this study did not involve participants with physical impairments or experience using assistive technologies. While our findings provide insights into general perceptions of PARs, future research should include individuals who are more representative of the intended user population to improve the utility of the results for PAR development. Fourth, we focused on the perception of a subset of motion parameters and assistive tasks in the U.S. Future work can evaluate other movement variables (e.g., force or trajectory) and assistive tasks. Also, as touch is a culturally interpreted, non-verbal form of communication, future studies should investigate whether cultural differences influence responses to PARs by studying populations beyond the U.S. Finally, we acknowledge that our study examined perceptions during initial interactions with PARs, yet assistive robots are typically used over extended periods. We focused on first interactions because there is limited research on how users initially respond to PAR motion, an essential baseline before examining longer-term shifts in perception. Future longitudinal studies will build on these findings to investigate how familiarity and trust develop over time, providing a more comprehensive understanding of users' evolving attitudes toward assistive robots.

7 Conclusion

We explored the use of online video-based crowdsourcing to evaluate user perceptions of a PAR across three different caregiving scenarios. Our results indicated that people's perceptions toward the PAR are complex and highly context-dependent, varying based on specific factors such as the task being performed, the proximity of the robot to sensitive areas of the body, and the characteristics of the robot's movements. Also, we found the influence of pre-existing attitudes toward robots on both the ratings of social attributes and emotional responses during the interaction. This study underscores the value of crowdsourcing as a scalable tool for gathering user data about PARs.

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