Evaluating Social Perception of Human-to-Robot Handovers Using the Robot Social Attributes Scale (RoSAS)

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ABSTRACT

This work explores social perceptions of robots within the domain of human-to-robot handovers. Using the Robotic Social Attributes Scale (RoSAS), we explore how users socially judge robot receivers as three factors are varied: initial position of the robot arm prior to handover, grasp method employed by the robot when receiving a handover object trading off perceived object safety for time efficiency, and retraction speed of the arm following handover. Our results show that over multiple handover interactions with the robot, users gradually perceive the robot receiver as being less discomforting and having more emotional warmth. Additionally, we have found that by varying grasp method and retraction speed, users may hold significantly different judgments of robot competence and discomfort. With these results, we recognize empirically that users are able to develop social perceptions of robots which can change through modification of robot receiving behaviour and through repeated interaction with the robot. More widely, this work suggests that measurement of user social perceptions should play a larger role in the design and evaluation of human-robot interactions and that the RoSAS can serve as a standardized tool in this regard.

CCS CONCEPTS

• **Computer systems organization** → **Robotics**; • **Human-centered computing** → **User studies**; **User centered design**; • **General and reference** → *Measurement*; Validation;

KEYWORDS

Human-Robot Interaction; Human-Robot Handovers; Handovers; Social Perception; Measurement; Robots; Robotics; Psychometric Scale; Social Robots; Social Robotics

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1 INTRODUCTION

The ability of robots to safely and effectively pass and receive objects is a crucial capability for collaborative human robot interaction. It is a skill that will allow robots to be increasingly useful in contexts ranging from manufacturing to assistive care. In particular, handovers with robots passing objects to human agents have previously been well studied. As robots are often tasked with delivering objects, most work places the robot in the giver role. Here, we focus on the reverse: handovers from humans to robots and, in particular, how users perceive the robot in this receiver role.

The goal of our work to gain a deeper understanding of robots in a receiver role and how factors influence users' behaviours and perceptions of the robot. We posit that examining social perceptions of collaborative robots is an important, yet understudied aspect of human-robot interactions (HRIs) as such perceptions often shape how these interactions takes place. To illustrate with a simple example, users may choose to give wide berth to a robot using fast, jerky trajectories that is perceived to be behaving aggressively, whereas users may choose to draw near to interact with a robot moving slowly and smoothly, perceiving it to be friendly and docile.

The study we present here examines how human collaborators perceive their robotic counterparts from a social perspective during object handovers - specifically, we explore how changing conditions affecting how the robot receives an object may change user opinion of the robot. For this work, we use the Robotic Social Attributes Scale (RoSAS) which was recently developed by Carpinella et al. [7].

2 BACKGROUND

2.1 Handovers

Prior work studying handovers has mainly been focused on human-to-human and robot-to-human handovers. Among these studies, there seems to be no consensus on which set of factors are important in determining how handovers are conducted; rather, a survey of the literature indicates that a multitude of unique factors affect how a handover is carried out by participants. Many studies considered how seemingly inconspicuous factors can play an important role in coordinating and directing handovers [1, 4, 5, 9, 16, 21, 22, 28, 29]. For example, multiple studies have found that gaze and eye contact for both humans and anthropomorphic robots can affect timing and coordination of handovers [1, 22, 28, 29]. Another stream of work has examined how grip and load forces plays an important part in allowing givers and receivers negotiate handovers leading to insight into the roles participants assume within a handover interaction [9, 18]. Other studied factors include arm kinematics and movement timing [1, 5], proxemics [4, 19] and handover object orientation [2, 8].

Since the number of factors within design space for human-to-human and robot-to-human handovers appears vast, we would expect that the design space for human-to-robot handovers would be no different, although largely unexplored. In this work, we begin by delving into factors we expect could affect perceptual judgments of the robot receiver, measured using the RoSAS.

2.2 The Robotic Social Attributes Scale (RoSAS)

In prior work, several studies of HRI have employed the Godspeed scale to measure user perception of robots. Developed by Bartneck et al., the Godspeed scale features five dimensions for rating robots: anthropomorphism (human-like vs machine-like), animacy (how life-like the robot appears or behaves), likeability (how friendly a robot seems), perceived intelligence, and perceived safety [3]. However, despite its widespread appeal, Ho and MacDorman and Carpinella et al. have found shortcomings to the scale including: lack of empirical work examining its psychometric properties, occurrences where scale items are confounded with positive and negative affect, situations where items do not correspond to the underlying constructs they are meant to measure, high correlations between constructs, and multidimensionality of some item pairings [7, 14].

Thus, in an effort to provide a more valid scale, Carpinella et al. developed the Robotic Social Attributes Scale (RoSAS) which attempts to address these issues through exploratory factor analyses and empirical validation. The RoSAS is a social psychometric instrument aimed towards measuring social perception and judgments of robots across multiple contexts and robotic platforms [7]. The development of the RoSAS is based upon the Godspeed scale and claims to improve cohesiveness, eliminate unnecessary dimensions through factor analysis, and not be tethered to specific types or models of robots. The scale measures three underlying robotic attributes - competence, warmth, and discomfort using 18 items which are shown in Table 1. While the scale borrows the competence and warmth attributes from more standard psychometric instruments used in social psychology measuring social perception [11], work in [7] shows that evaluations of robots are somewhat more complex, employing the third, discomfort attribute that is additionally measured by the RoSAS. In Carpinella et al.'s work, the scale was validated via a study which had participants evaluate gendered human, robot, and blended human-robot faces shown on a screen. In contrast, this work proposes to use the RoSAS to evaluate a physical HRI.

Table 1: Table of RoSAS items testing each attribute.

Competence	Warmth	Discomfort
Reliable	Organic	Awkward
Competent	Sociable	Scary
Knowledgeable	Emotional	Strange
Interactive	Compassionate	Awful
Responsive	Happy	Dangerous
Capable	Feeling	Aggressive

The RoSAS has been chosen for this work as it provides a empirically validated method of measuring how users perceive their robotic counterpart. Additionally, as the RoSAS shares the competence and warmth dimensions with measures of social perception of people, it allows for intuitive comparisons and extrapolation of how the robot may be matched against a human in terms of these dimensions.

3 EXPERIMENTAL DESIGN

As this work is mainly an exploration of design space for robot receiving during handovers, we selected a limited number of variables from a potentially large pool to test. To aid in this selection, we chose factors that affect the chronological beginning, middle, and end of the handover. Three factors emerged as the variables for robot receiving during handovers during a pilot study: initial position of the arm prior to handover, grasp type, and retraction speed following handover.

3.1 Initial Position of the Arm Before Handover (*Down* and *Up*)

For this factor, we modify the initial arm position of the robot displayed to the giver prior to handover. Two positions are used which are labeled *up* and *down*. Both initial positions are shown in Figure 1. We have chosen to examine initial arm position as a factor since we expect that differences here may affect giver behaviour when they are reaching out to indicate where and when a handover takes place. For example, the *up* position could convey the robot is awaiting the handover object, whereas the *down* position might suggest that the robot has not yet recognized the givers intent. They also present slightly different initial spacing the between the robot end effector and user, which may affect where the handover takes place as indicated by Huber et al. and Basili et al. in [4, 15].

3.2 Grasp Type During Handover (*Quick* and *Mating*)

Motivated by prior studies on haptic negotiation in human-computer interaction which suggest that dynamic interactions

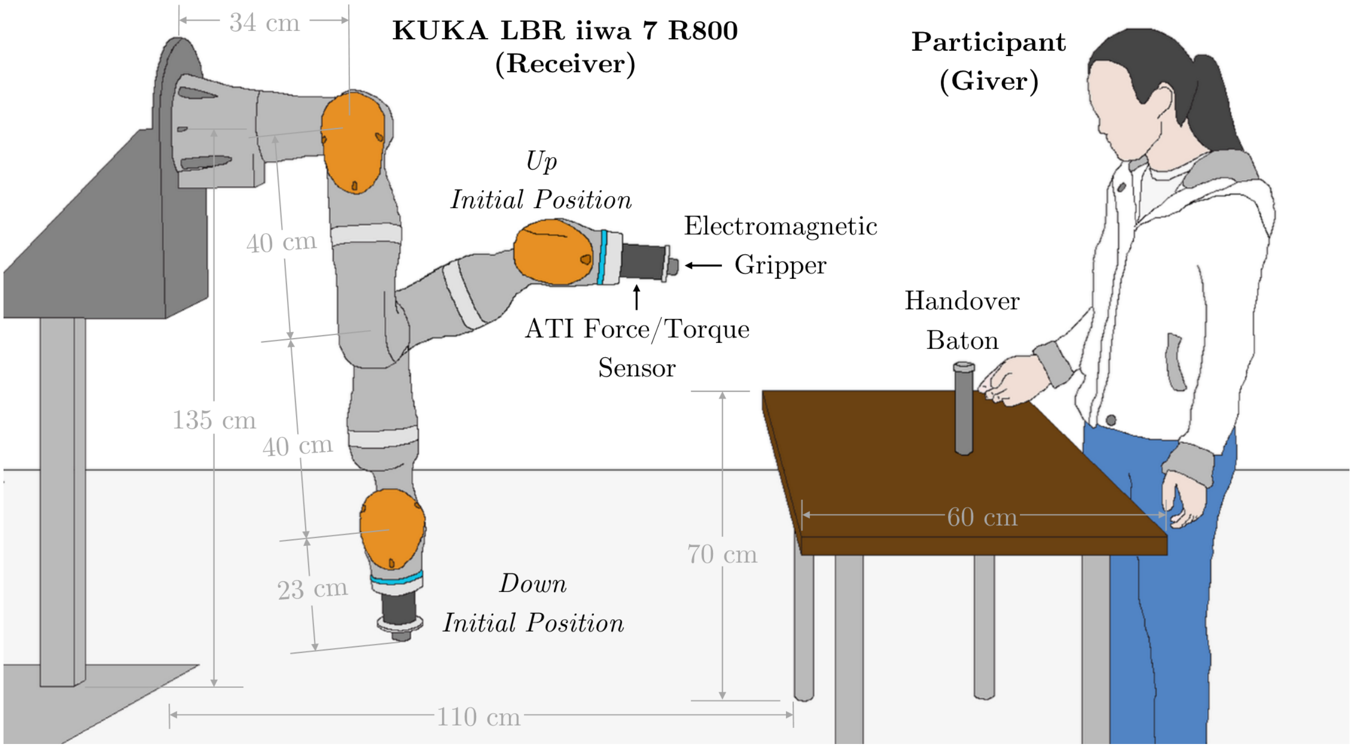

Figure 1: Experimental setup for handover experiment. Diagram shows both the *up* and *down* initial arm positions tested as conditions in the experiment.

are able to change how 'personal' and 'human-like' an interaction is [13, 23], robot grasping is examined as another factor in this work. Gripper design and grasping is still an active area of research. Much of this work tries to solve the problem of matching the speed, smoothness, dexterity and conformity of the human grasp. Current state-of-the-art grasping methods either carefully plan feasible grasps and execute them slowly, or applies brute force to 'robotically' grasp without the delicacy of human touch. Rather than focus on object grasping, we have decided to use a simple exctromagnetic interface, co-planar between the robot's tip and a baton (to be used as the handover object in the experiment). This allows us to emulate both extremes - speed and brute force can be both achieved by turning on the magnet in close proximity to the baton, creating sudden impulses due to minute misalignments. Alternatively, we can accommodate misalignments to create a smooth yet slow contact. In the *quick* grasp, the robot moves its electromagnetic end effector to within 1 cm distally from the cap of the baton during a handover. As soon as the 1 cm threshold is met, the electromagnet is activated and draws in the baton. In the *mating* grasp, the robot deliberately moves all the way into contact with the baton. Then, based on measurements of an ATI Mini45 Force/Torque sensor (ATI Industrial Automation, Apex, North Carolina, USA) located in series with the electromagnet at the robot end effector (see Figure 1), it further adjusts its orientation to achieve flush contact. Only when the electromagnet is coplanar with the baton's cap is it activated. This behaviour allows the robot to ensure stable contact and thus safety of the object during handover before retracting. A flowchart of how these grasping behaviours are carried out can be found in Figure 2.

3.3 Retraction Speed Following Handover (*Slow* and *Fast*)

Retraction speed was selected as a factor for examination as prior work has shown that a robot's speed of movement seems to play a significant role in how human observers and collaborators subjectively perceive the robot [24, 27, 30]. For example, in an experiment conducted by Zoghbi et al., they found that fast robot motions were correlated with increased user arousal and decreased valence during self-reports of affect [30]. Thus, in this work, we hypothesized that retraction speed following handover may affect how users perceive the robot in terms of the RoSAS measures of warmth and discomfort, e.g., slow retraction speed may be rated as higher warmth and lower discomfort as opposed to higher speed which may lead to less warmth and greater discomfort. The *slow* setting was set to 10 cm/s, whereas 20 cm/s was set as the *fast* setting. These settings were designed to emulate a gentle tug and a firm yank.

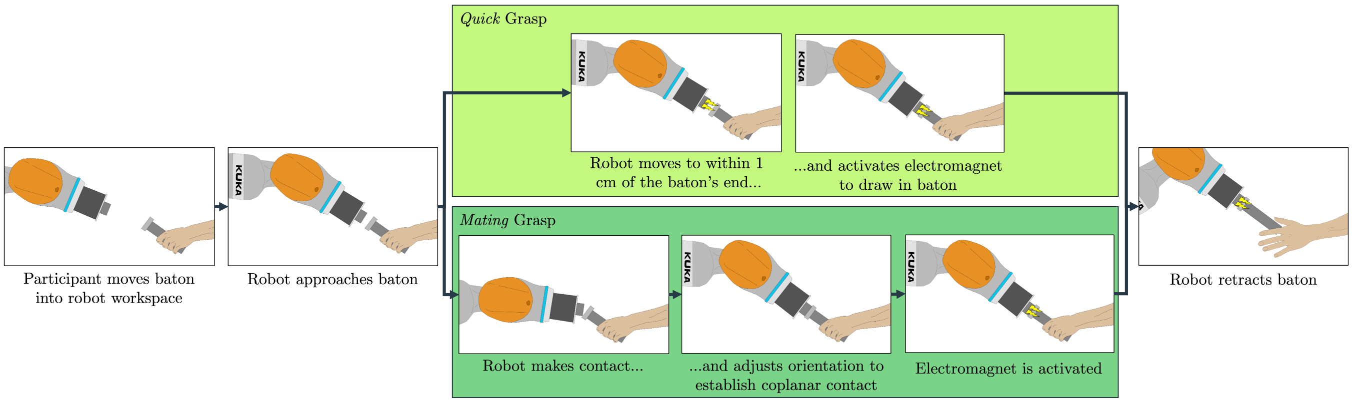

Figure 2: Flowchart of *quick* (top row) and *mating* grasp types. The *quick* grasp pulls in the baton magnetically while the *mating* grasp establishes coplanar contact, gently pressing against the baton before activating the magnet.

Table 2: Table of experimental conditions.

Condition	Arm Position	Grasp Type	Retraction Speed
1	*Down*	*Quick*	*Slow*
2	*Up*	*Quick*	*Slow*
3	*Down*	*Quick*	*Fast*
4	*Up*	*Quick*	*Fast*
5	*Down*	*Mating*	*Slow*
6	*Up*	*Mating*	*Slow*
7	*Down*	*Mating*	*Fast*
8	*Up*	*Mating*	*Fast*

3.4 Conditions

We use a 2x2x2 experiment design to test these factors, which form 8 conditions as shown in Table 2. We chose these factors not only to see how they affected user perception of the robot's attributes, but also to study how they influenced proxemics and kinodynamics of the handover interaction. For example, it was hypothesized that examining initial arm position could help determine how people approach and direct handover gestures to a disembodied robot arm and how these gestures compare to human receivers studied in prior work [4, 26]; retraction speed and grasp type were selected to research the force/torque interaction between the giver and receiver and to establish what dynamic negotiations occur during human-to-robot handovers. Although beyond the scope of this manuscript, the investigations examining these aspects of this experiment are presented in [25].

4 EXPERIMENT SETUP

4.1 System

A KUKA LBR iiwa 7 R800 robot (KUKA, Augsburg, Germany) was used in this study to receive objects from participants. The robot was mounted as shown in Figure 1, 135 cm above ground level and fitted with a simple electromagnetic gripper. When activated, the gripper allowed the robot to securely grasp a handover baton via coplanar interfacing with a ferromagnetic cap mounted to the top end of the baton.

We use a set of 12 OptiTrack Flex 13 motion capture cameras (NaturalPoint, Corvallis, Oregon, USA) to track objects within an approximately 3x3 m space. Each tracked object uses a unique constellation of retroreflective markers. We track the user's hand, handover object (baton), and robot end effector. The Flex 13 cameras have a frame rate of 120 frames per second with an average latency of 8.33 ms (as reported by OptiTrack's Motive software). Position and orientation tracking data of each object is transmitted via UDP to a second computer controlling the robot's behaviour.

For our system, we used a handover model which stipulated that the robot receiver reacts to the giver. Thus, in our study, we had participants initiate the handover by holding out the baton towards the robot, similar to how handovers have been initiated in previous studies [26]. The robot checked to see if the baton is in its reachable workspace; if so, the robot then proceeded to move to grasp the object from its initial position. Once certain grasp conditions are met as determined by the grasp type, the robot activated the electromagnet and began retracting the arm and baton by 10 cm, before moving into the arm down position (see Figure 1). If, at any point during the retraction and movement to the arm down position, the system detects that the baton had not being grasped (i.e., the giver did not release the baton and overcame the electromagnet), the robot immediately returned to the baton to reattempt grasping.

4.2 Participants

This study was reviewed and approved by the Disney Research Institutional Review Board. A priori power analyses were conducted to determine the sample size required for this study. With $\alpha = .05$, we concluded that a sample size of at least 20 was needed to detect a moderate effect size ($\eta^2_{partial} = .13$) with 90% power ($1 - \beta$) [10]. Recruitment was performed within Walt Disney Imagineering Advanced Development and Disney Research. Twenty-two participants

(11 females, 11 males), aged 22-52 years [M = 30.32, SD = 8.12] were recruited in total. All participants provided their informed consent prior to the experiment; they were notified that their participation was voluntary, and they were allowed to withdraw from the experiment at any time. Additionally, we obtained permission from all participants to record both video and motion capture data from the experiment. No reward was given for participation in this study.

4.3 Participant Task

At the start of each experiment session, participants were led into the motion capture space and asked to wear a motion-tracked glove on their dominant hand. They were asked to stand behind a table, as shown in Figure 1, to reduce any likelihood of injury to participants by restricting their body (except the hand holding the baton) from entering the robot's reachable workspace.

For each trial, participants picked up the baton off the table and initiated a handover to the robot after hearing the experimenter say 'go'. Upon detecting the baton in its workspace, the robot would move to retrieve the baton in a way that was consistent with the condition being tested. Three trials were performed for each condition (3 trials * 8 conditions = 24 trials in total per participant). Following each set of three handover trials for a condition, participants were asked to complete the full RoSAS inventory which asked them to rate how closely each of the 18 items associated with the robotic handovers they just performed. Ratings were on a scale from 1 to 7 where 1 was 'not at all', 4 was 'a moderate amount', and 7 was 'very much so'.

Conditions were counterbalanced between participants using a Latin square design to prevent carry-over effects. Each experiment session lasted approximately 30 minutes.

5 RESULTS

5.1 RoSAS Internal Consistency and Dimensionality

As the RoSAS is a relatively new scale that has not yet been applied to human-robot interactions [7], we conduct an internal consistency test to confirm the results of the exploratory factor analysis performed by Carpinella et al. Internal consistency measures how closely the RoSAS inventory items fit within the three attributes (competence, warmth and discomfort) using the data in this study. For testing, Cronbach's alpha was used; an $\alpha_{Cronbach} \geq .80$ is considered to represent high scale reliability. Items for competence ($\alpha_{Cronbach}$ = .90), warmth ($\alpha_{Cronbach}$ = .94) and discomfort ($\alpha_{Cronbach}$ = .81), all scored above this threshold suggesting that the items have relatively high internal consistency within their respective attributes.

In addition to investigating consistency, dimensionality of each attribute of the RoSAS were considered as well. Unidimensionality indicates that the items of each attribute measure and correspond to only one dimension of the scale. On the other hand, if two or more items are needed to explain the majority of the variance within one attribute, this

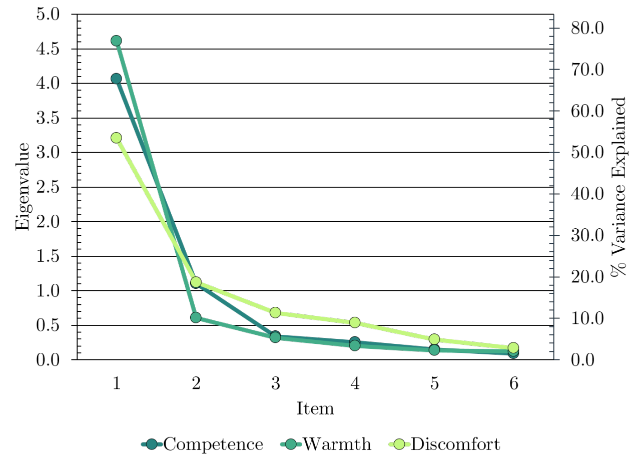

Figure 3: Factor analysis scree plot for RoSAS attributes.

attribute would be multidimensional; this would invalidate the RoSAS as the attribute would also be measuring and combining distinct aspects. A factor analysis was performed to ensure that the attributes are unidimensional. Eigenvalues represent how much variation in each attribute is explained by each item were examined; the larger the eigenvalue, the more variation the item explains. For an attribute to be unidimensional, one would expect to see one item account for a large portion of the variance within the attribute, and other items account for much less variation. As shown in Figure 3, the results show that the first items in competence, warmth and discomfort attributes explains 67.7%, 76.9%, and 53.5% of the variance respectively. Given that a majority of the variances are explained by one item within each attribute, our findings suggests that each attribute is unidimensional.

5.2 Effect of Conditions

A three-way repeated measures MANOVA was conducted to test the effect of the manipulated variables (initial arm configuration, speed of retraction, and grasp type) on the RoSAS attributes (Figure 4). Effect sizes in terms of partial eta squared ($\eta^2_{partial}$) are reported [1].

Significant main effects of grasp on reports of competence [F(1,21)=25.660, p<.001, $\eta^2_{partial}$ =.550] and discomfort [F(1,21)=7.485, p=.012, $\eta^2_{partial}$ =.263] were found. The latter effect is qualified by a significant interaction effect of speed by grasp on reports of discomfort [F(1,21)=7.360, p=.013, $\eta^2_{partial}$ =.260]. A post hoc pairwise comparison indicates that the average competence score for the *quick* [M = 5.225, SD = 0.980] grasp type is 1.017 points higher than the *mating* [M = 4.208, SD = 1.135] grasp type [p < .001], representing a large effect size [d = 0.835]. No other main or interaction effects were found to hold statistical significance.

[1] As a rule of thumb, Cohen indicates that partial eta square values of .0099, .0588, and .1379 may serve as benchmarks for small, medium, and large effect sizes [10].

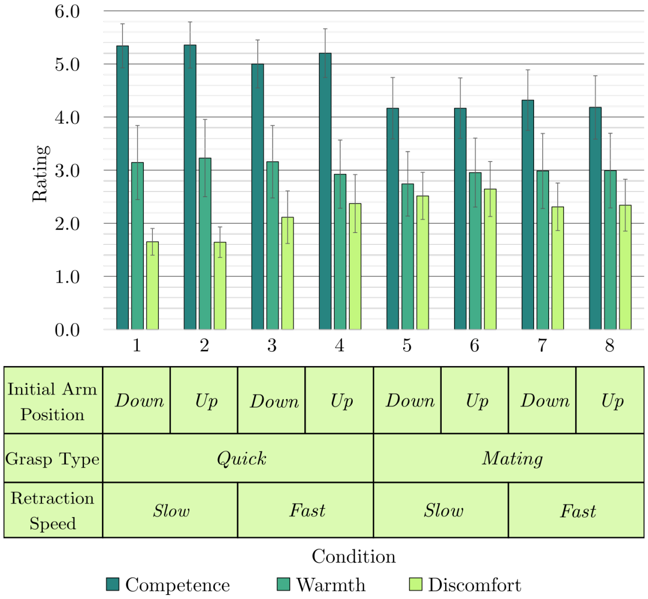

Figure 4: Participants ratings of the robot's competence, warmth and discomfort over condition. Error bars represent 95% CIs.

The significant retraction speed by grasp interaction effect (Figure 5) was further investigated using paired t-tests at levels of retraction speed (α = .025). A significant difference in discomfort scores between the fast [M = 1.648, SD = 0.638] and *mating* [M = 2.580, SD = 1.140] grasp types was found at low speed [T(43)=2.621, p<.001, d=1.048]. No significant difference in discomfort scores between quick [M = 2.242, SD = 1.241] and *mating* [M = 2.326, SD = 1.108] grasp types was found at high speed [T(43)=0.370, p>.05, d=0.072]. There was also a failure to detect a significant difference between scores at slow and fast retraction speeds for the *mating* grasp.

5.3 Effect of Repeated Interaction over Time

Although the presentation order of conditions was counterbalanced across participants, we wanted to determine if participants' perception changed over the course of repeated handover interactions with the robot. To examine this effect, we categorized participants' trials by the order in which they were presented in time rather than by experimental condition as shown in Figure 6. Trend analysis, a statistical test based upon the F-statistic that is an alternative to an ANOVA [12], was conducted for each attribute with appropriate corrections for non-spherical data. Results showed a significant positive linear trend for warmth [F(1,21)=7.375, p=.013, $\eta^2_{partial}$ =.260] and negative linear trend for discomfort [F(1,21)=6.442, p=.019, $\eta^2_{partial}$ =.235]; no significant linear trend was detected for competence. Higher order trends were non-significant for all attributes.

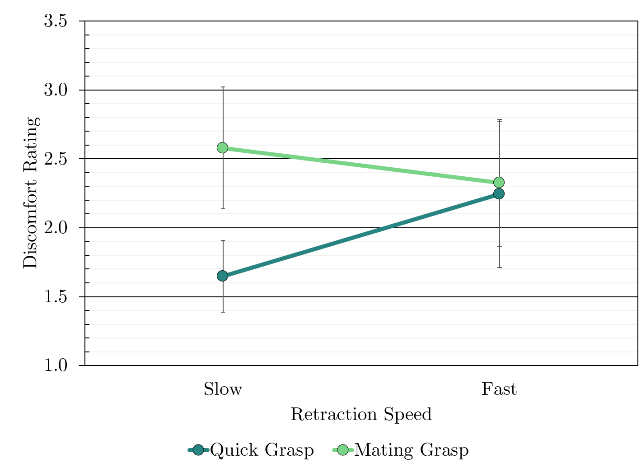

Figure 5: Interaction plot showing participants ratings of the robot's discomfort based on grasp type (*quick*, *mating*) at levels of retraction speed (*slow*, *fast*). Error bars represent 95% CIs.

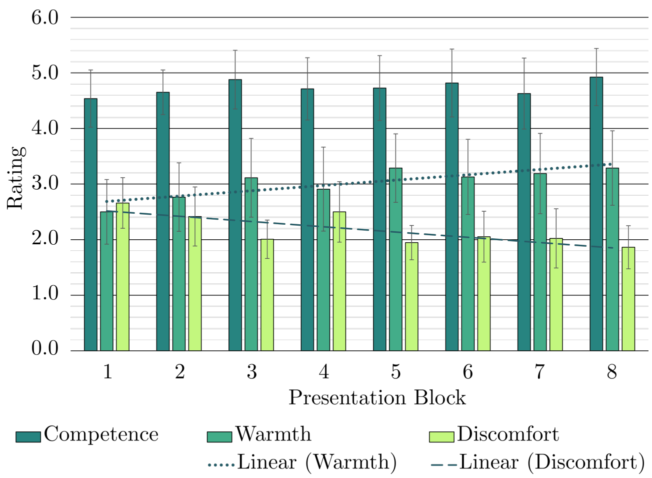

Figure 6: Participants ratings of the robot's competence, warmth and discomfort over time (segmented into condition presentation blocks). Linear trend lines for warmth and discomfort attributes are shown. Error bars represent 95% CIs.

6 DISCUSSION

6.1 RoSAS Internal Consistency and Dimensionality

Carpinella et al. claims in [7] that "RoSAS provides a psychometrically validated, standardized measure that can be used to measure robots developed by different people in different places for differing purposes and over time." As this is the first known usage of the RoSAS for human-robot interaction, we felt it important to examine the integrity of the scale as it applies to data collected in this study. Although a full validation of the RoSAS using confirmatory factor analysis was not performed due to our modest sample size, examination of the results show that the 18 items of the scale conform to the three measures of the scale - competence, warmth and discomfort - with a high degree of consistency. Additional testing showed that the attributes were highly unidimensional. Thus, the results suggests that the application of RoSAS for this work, and perhaps more generally to other human-robot interactions, appears to be valid. However, more work is needed to concretely confirm the validity of using RoSAS for other HRIs.

6.2 Effect of Conditions

As shown by the results, grasp type had a significant and large effect on competence scores, with the *quick* grasp scoring significantly higher than *mating* grasping. This find runs contrary to our expectation that having the robot ensure the handover object's safety through stable contact would demonstrate more intelligent/competent behaviour. One explanation for this finding is that although the *mating* grasp demonstrates more intelligent algorithms to ensure handover object safety, users may actually find the method to be a significant departure from handovers between human participants compared to the *quick* grasp; thus, they not able to adapt easily to this novel method of handover. For example, in human-human handovers, receivers apply pulling/tugging forces to the object which signal to the giver to release the object [9]. As opposed to the *quick* grasp, the robot initially applies pushing forces to the object in the *mating* grasp, which runs contrary to expectation and leads to confusion. As evidence for this, review of video recordings show participants complying to the robot pushing against the baton.

An alternative but complementary explanation for the phenomenon relates to trade-offs made by each grasp type: the *quick* grasp trades off object safety for efficiency in terms of time to complete the handover, whereas *mating* does the opposite. Having faster, more seamless handovers may factor more into competence scores than ensuring object safety, particularly if the role of maintaining the object's safety throughout the handover is the giver's responsibility rather than the receiver's as suggested by Chan et al. [9]. In this case, having both participants in the handover be responsible for object safety may feel redundant to the user.

As seen from the results, we also detected a significant retraction speed by grasp interaction effect on discomfort scores. Analysis of this interaction effect suggests that for the *mating* grasp, the discomfort rating was unaffected by retraction speed, whereas the *quick* grasp increased discomfort to within the same range as the *mating* grasp in the *fast* retraction speed condition. This may be due to object safety being doubly compromised by both the *quick* grasp type and *fast* retraction which emphasizes speed over safety causing participants to feel that the robot appears too 'brash' (as one participant was quoted) in how the object is handled by the robot during the handover. It appears that the *quick* grasp coupled with *slow* retraction was rated less discomforting possibly due to increased time for the giver to ensure that the baton is securely grasped by the robot during the retraction phase of the handover. It is possible that discomfort decreased only when both grasp and retraction speed matched their expectations. To further explore if this is indeed the case, we plan on analyzing force/torque data collected during the study as future work.

As opposed to retraction speed and grasp type, we failed to detect any main effects of initial arm position on any of the RoSAS attributes. Although this result may be due to small sample size and consequently lack of power, obtained effect sizes indicate that the magnitude of the effect of varying arm position is extremely small for the attributes of competence and warmth ($\eta^2_{partial} < .004$), and small-medium for discomfort ($\eta^2_{partial} = .051$) when applying Cohen's benchmarks [10]. This suggests that user perception of robot competence and warmth may be better informed by the robot's dynamic behaviours rather than static poses; a study with larger sample size would be needed to determine if the moderate effect of robot pose on ratings of discomfort is significant. However, we posit that initial position may still impact on timing and location of the handover, as well as how the negotiation during handover is accomplished. Thus, we plan on analyzing the collected kinematic data to determine if such effects exist.

6.3 Effect of Repeated Interaction Over Time

Examination of participants evaluations of the robot's competence, warmth, and discomfort over repeated interactions showed a significant linear increase in warmth and linear decrease in discomfort; both of these trends were observed to have a large effect size indicating the prominence of these observations. These findings suggests that the more people interact with the robot, the more they develop positive attitudes towards the robot. The development of familiarity or affinity towards robots is not at all surprising to see as other studies have shown this phenomenon to occur in other contexts such as in assistive home care [17, 20] or military robotics [6]. However, the observation of linear trends in both ratings of warmth and discomfort over time is a notable result. This leads us to wonder if changing interaction parameters or attributes of the robot's receiving gestures could lead to changes in trend rates for warmth/discomfort ratings. If so, these parameters may be tuned or optimized to obtain a fast increase for warmth ratings and decrease for perceived discomfort levels. In turn, this may provide some benefits to having inexperienced users feel comfortable interacting with robots that may appear imposing or foreign - i.e., quickly having factory workers become comfortable working with collaborative industrial robotics. Further study is required.

Failing to detect any significant trends in ratings of competence over time coupled with small effect size ($\eta^2_{partial} < .018$) suggests that how competent or able a robot appears to users is not a function of repeated interaction, but rather simply of behaviours attributed to the robot, as seen by the significant main effect of grasp type on competence.

6.4 Implications for Human-Robot Interactions

Although this work focuses on handovers, some results observed may have wider implications for other HRIs.

Short of full validation, the RoSAS was shown to be internally consistent and unidimensional across attributes. This result is promising in that it suggests that the scale may be used to similarly evaluate user social perceptions of other HRIs, and thus has the potential to perform as a standardized metric. Additionally, the RoSAS can serve as a valuable tool for aiding in the design and evaluation of robot appearances and behaviours by way of allowing users to provide subjective input by way of a proven framework.

The effects that were observed with grasp and retraction speed impacting people's perceptions of the robot's competence and discomfort may have broader implications for HRI in terms of the trade-offs they present - e.g., faster interaction during HRI may be more efficient, but may cause greater discomfort to users, and seemingly more intelligent behaviours by the robot may not be perceived as such due to decreased efficiency of the interaction. Thus, these observations highlights the importance of considering user perceptions when efforts to develop HRIs which add efficiency or capabilities are undertaken.

Lastly, the observation of trends over repeated interactions with the robot may not be isolated to just the handover use case. The finding that the more that users interact with the robot, the more they develop positive affect towards the robot may just as likely with other HRIs. Thus, this implies that examining inexperienced participants reactions during studies of HRIs may not be as important as considering longitudinal effects and how fast people's perceptions change over repeated interactions.

7 CONCLUSIONS AND FUTURE WORK

In this work, we have performed a study of human-to-robot handovers examining the social perceptions that users have of the robot, and how these perceptions change in response to modifications to the robot's kinodynamic behaviours during the handover. These perceptions were measured using the RoSAS tool developed in [7]. A post hoc factor analysis and assessment of the dimensionality of the tool's attributes indicate that the RoSAS appears to be an acceptable instrument for evaluating the subjective experiences in the handover task and perhaps for other physical HRI contexts as well.

Using the RoSAS, we have found that by varying simple parameters such as arm retraction speed following handovers and grasping behaviour, users can hold significantly different views on social qualities of the robot in terms of competence and discomfort. Ironically, even though the robot demonstrated a more intelligent grasping strategy in the *mating* grasp compared to the *quick* grasp, participants perceived the robot as being less competent and more discomforting. Thus, seemingly intelligent robot behaviours doesn't necessarily constitute competent or comfortable behaviours in the eyes of users. It appears, rather, that interaction efficiency and/or similarity to human-human handovers (at least in terms of force profiles) constitutes a larger part of establishing more positive user affect when working with the robot. Also, we have detected that users perceive robots as being less discomforting and having more emotional warmth the more exposure they have to handover over objects to the robot. We believe this may apply to other human-robot interactions as well.

The results presented here offers a glimpse into how users ascribe social attributes to robots during collaborative tasks and how RoSAS can be used to evaluate these perceptions. Our hope is that the results of this study may inform other human-robot interactions which can be similarly evaluated.

As discussed in the analysis, the results of this study have generated more research questions and numerous pathways for further exploration. Using additional data collected from this study, we have investigated how the kinodynamics of human-to-robot handovers are affected by the factors of initial arm position, grasp type, and retraction speed (presented in [25]). As future work, we wish to determine whether similarities or differences exist between human-human and human-robot handovers. Previously, Chan et al. established that both participants in a handover implicitly take up roles during the handover negotiation where the giver is responsible for the safety of the object and the receiver is responsible for the efficiency and pace of the handover [9]. We aim to determine if these roles also exist within the framework of human-to-robot handovers. Furthermore, with regards to the RoSAS, we plan on expanding its use for other HRIs to obtain further substantiation of its validity and to explore how social perceptions could/should shape such interactions.

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