Comparing Subjective Perceptions of Robot-to-Human Handover Trajectories

Alexander Calvert
Monash University, Australia
acal0003@student.monash.edu

Wesley P. Chan
Monash University, Australia
wesley.chan@monash.edu

Tin Tran
Monash University, Australia
trung.tran@monash.edu

Sara Sheikholeslami
University of British Columbia, Canada
ssheikho@mail.ubc.ca

Rhys Newbury
Monash University, Australia
Australian National University, Australia
rhys.newbury@monash.edu

Akansel Cosgun
Deakin University, Australia
akan.cosgun@deakin.edu.au

Elizabeth Croft
University of Victoria, Canada
croft@uvic.ca

Abstract
Robots must move legibly around people for safety reasons, especially for tasks where physical contact is possible. One such task is handovers, which requires implicit communication on where and when physical contact (object transfer) occurs. In this work, we study whether the trajectory model used by a robot during the reaching phase affects the subjective perceptions of receivers for robot-to-human handovers. We conducted a user study where 32 participants were handed over three objects with four trajectory models: three were versions of a minimum jerk trajectory, and one was an ellipse-fitting-based trajectory. The start position of the handover was fixed for all trajectories, and the end position was allowed to vary randomly around a fixed position by ±3cm in all axis. The user study found no significant differences among the handover trajectories in survey questions relating to safety, predictability, naturalness, and other subjective metrics. While these results seemingly reject the hypothesis that the trajectory affects human perceptions of a handover, it prompts future research to investigate the effect of other variables, such as robot speed, object transfer position, object orientation at the transfer point, and explicit communication signals such as gaze and speech.

1 Introduction
Over the last few decades, robots have become more prevalent in various applications, including manufacturing [Tan et al., 2009], healthcare [Kyrarini et al., 2021], and home-care [Portugal et al., 2015]. Their use is projected to increase over the coming decade [Robotics Australia Group, 2022], requiring significant research and investment to ensure that robots can effectively integrate into human environments. One vital task that service robots need to perform frequently is object handovers with humans. An object handover is a collaborative task and involves an agent (the giver) handing an object over to another agent (the receiver). Since handovers are an essential part of our daily lives, robot-human handovers need to be a smooth, efficient, effective, and an enjoyable
experience for humans.

In human-robot handovers, the human worker’s selection of anticipatory actions has a temporal dependency on the robot’s actions and is based on predictions of the future state of the robot’s motion [Dragan et al., 2013]. Such collaboration requires legible (intent-expressive) co-ordination of the specific behavior of human-robot handovers. As the robot reaches out to handover an object, the collaborator should be able to tell early on and reach out to meet the robot’s hand.

Changing the style of the robot’s motion to match the task it is performing also improves perception [Zhou and Dragan, 2018]. As expectations strongly influence perception, robots need to perform handover motions to match the expectations and preferences of the human interacting with the robot [Bestick et al., 2018]. For example, a human would expect the robot to be confident while opening a door but cautious when handling a fragile object, resulting in two different motion styles.

Researchers investigating the reaching motion used by robots have found that human-like handover behavior is preferred [Shibata et al., 1997], and can result in quicker and more efficient handovers [Huber et al., 2008]. Several human-like reaching motion models have been proposed and used in object handover research, including the minimum jerk model [Hogan, 1982], the decoupled minimum jerk model [Huber et al., 2009] and more recently, the elliptical model [Sheikholeslami et al., 2018]. In our previous work, we compared these models to several datasets of human-giver reaching trajectories to investigate which model best fits the reaching motion of a human, finding that the elliptical model was more human-like compared to the minimum jerk models [Sheikholeslami et al., 2018; Chan et al., 2021]. However, these models are yet to be compared via a robot-human handover task. Hence, this paper aims to compare these models via a user study to establish which motion model is preferred by a human agent collaborating with a robotic system.

Figure 1: We compare the subjective experience of robot-to-human handovers for a range of motions.

2 Related Works

2.1 Communication in Human-Robot Handovers

A survey by Ortenzi et al. [2021] found that only a minority of human-robot handover works consider communication cues. However, communication cues are critical in initiating and co-coordinating joint actions such as object handover [Strabala et al., 2013]. These cues are often non-verbal and are modeled after human behavior.

Several works have found that human-like gaze behaviors in robots can improve the timing of handovers. Moon et al., 2014; Zheng et al., 2015. Gaze has also been shown to convey intent before a handover begins [Strabala et al., 2013]. Admoni et al. [2014] decreased the speed of the handovers until the human gaze was drawn back to the robot, which increased the conscious perception of the communication cues. In Grigore et al. [2013], the authors integrated both head orientation and eye gaze into the robot’s decision-making and showed that this significantly increases the success rate of robot-to-human handovers. The use of body gestures Cakmak et al., 2011 and the initial pose of the robot Pan et al., 2018 can improve the subjective experience of the handover.

2.2 Handover Motions

The motion of the robot arm during the handover has also been shown to significantly affect subjective user experience during object handovers Shibata et al., 1997. Research has shown that humans can perceive the robot as safer and more pleasant when using human-like trajectories Shibata et al., 1997; Huber et al., 2008. In addition, human-like reaching motions can enable the prediction of the handover location, resulting in more timely and efficient handovers [Glasauer et al., 2010].

Given that object handovers can happen at any time, and with varying start and end positions, the reaching motion employed by a robot must be generated efficiently, requiring a model which can be computed in real-time. This requirement limits the number of models which are suitable for object handover.

The Minimum Jerk trajectory model was first proposed by Hogan in the early 1980s Hogan, 1982 and has been used extensively to model human handover motion, including in recent works such as Pan et al. [2019a]. The Minimum Jerk model assumes that the path taken during a handover is straight; however, it was later shown that human handover motions follow a curved path Huber et al., 2009. To allow for a curved path, Huber et al. [2009] proposed the Decoupled Minimum Jerk model. This model creates a curved path by decoupling the reaching motion into two separate Minimum Jerk trajectories. More recently, Sheikholeslami et al. [2018] proposed an elliptical motion model that is shown to yield...
a good fit to human motion in seated single-person pick-and-place tasks. Research has also investigated whether this model fits the human motion in unconstrained object handover, showing that the elliptical model fits the motion accurately [Chan et al., 2021].

3 Trajectory Generation Models

The scope of this work is limited to the trajectory that the robot arm takes between the point the object is first grasped from the table and the object transfer point, which is fixed in all experiments. We compare four trajectory models, each described in this section.

3.1 Minimum Jerk

The Minimum Jerk model hypothesizes that human arm motion between two points in space minimizes the jerk over the entire path, which implies a straight line path between the start and end points of the trajectory. The decoupled minimum jerk model can be specified by boundary conditions and the desired duration where the coefficients \( a \) are determined by the boundary conditions, i.e., the position, velocity, and acceleration at the start and end points of the trajectory.

3.2 Decoupled Minimum Jerk

The Decoupled Minimum Jerk model can be specified by two Minimum Jerk trajectories [Huber et al., 2009], one for the \( XY \)-plane motion and the other for the \( Z \)-axis motion, each with a different duration where the \( Z \)-axis is along the local vertical direction. The Decoupled Minimum Jerk trajectories are described by:

\[
\begin{align*}
    r_z(t) &= a_{0z} + a_{1z}t + a_{2z}t^2 + a_{3z}t^3 + a_{4z}t^4 + a_{5z}t^5, \\
    r_{xy}(t) &= a_{0xy} + a_{1xy}t + a_{2xy}t^2 + a_{3xy}t^3 + a_{4xy}t^4 + a_{5xy}t^5
\end{align*}
\]

where \( r_z(t) \) is the trajectory in the \( Z \)-direction, with duration \( t_z \), and \( r_{xy}(t) \) is the trajectory in the \( XY \)-plane, with duration \( t_{xy} \). Coefficients \( a_{iz} \) and \( a_{izy} \) are determined by boundary conditions and the desired duration of each component of the motion. The Decoupled Minimum Jerk trajectory is on a plane orthogonal to the \( XY \)-plane, and has a curved path in 3D space.

3.3 Elliptical Model

It has recently been empirically shown that an elliptical curve achieves a better fit to human reaching motions for both unconstrained [Chan et al., 2021] and constrained [Sheikholeslami et al., 2018] handovers. The equation for an ellipse can be expressed in parametric form, parameterized with \( \theta \), as:

\[
\begin{bmatrix}
    x(	heta) \\
    y(	heta)
\end{bmatrix} = \begin{bmatrix}
    x_c \\
    y_c
\end{bmatrix} + \begin{bmatrix}
    \cos(\tau) & -\sin(\tau) \\
    \sin(\tau) & \cos(\tau)
\end{bmatrix} \begin{bmatrix}
    \text{asec}(\theta) \\
    \text{atan}(\theta)
\end{bmatrix}
\]

where \( x_c, y_c \) is the centre of the ellipse, \( \tau \) is the roll angle and \( a, b \) are the semi-major and semi-minor axes respectively.

The dataset by [Chan et al., 2020] is utilized to fit the ellipse models. A subset of trajectories (76 out of 1195) was used, selecting only right-handed handovers and trajectories that fit the elliptical model well. Parameters in Eq. (5) were computed from the mean values of the trajectories in the dataset, along with the starting and ending points of the handover. The starting point is placed above the table top, to the right of the robot arm, while the ending point is set at the mean end position of the subset of trajectories.
Ellipses arise as second-degree curves generated by the intersection of a plane and a cone. Therefore, to justify an elliptical fit to the reach data, the reach trajectory must be planar [Chan et al., 2021]. The same subset of data was analyzed to find the normal vector for each trajectory to determine the best fit plane. We then used the mean normal vector and the known starting position to define the plane on which the robot’s motion would be generated.

An elliptical trajectory is then generated by specifying the dependence of $\theta$ on time. As the dataset provided by Chan et al. [2020] includes unconstrained handovers with non-zero initial velocity and acceleration, fitting a model to this dataset would result in the robot jerking rapidly at the start of the reaching motion. To prevent this, we utilized an additional dataset of handover reaching motions with zero initial velocity and acceleration. We normalized time and $\theta$ to be in the range [0,1] and fit a sigmoid function to the mean $\theta$ from this dataset to define an elliptical trajectory.

### 3.4 Slanted Decoupled Minimum Jerk

We included a new different type of trajectory, generated by specifying a Decoupled Minimum Jerk trajectory and rotating it to be on the same plane as the Elliptical Motion Model used. Adding this additional trajectory allows a more direct comparison of the Decoupled Minimum Jerk trajectory to the Elliptical Motion Model.

### 4 User Study Design

#### 4.1 Hardware

We use a 7-DoF Franka Emika Panda robotic arm controlled via Robot Operating System (ROS). An OAK-D camera operating at 60Hz was utilized to record the participants whilst they completed each handover, with the data recorded used for post-analysis to determine the location of the user’s hand during the handover. Participants wore a red band on their right wrist, allowing easy hand tracking.

#### 4.2 Task Description

To hand over the objects to the receiver, the robot first moves from a home position to a fixed position above the objects. It then picks up an object and moves to a fixed starting position. The robot then utilizes a handover motion model to hand the object over to the receiver. Once the robot reaches the object transfer point, it waits for the user to take the object, pausing for 1 second before moving back to the home position.

Research has shown that a handover typically occurs in approximately 1.2 seconds [Chan et al., 2020]. Due to constraints on the joint velocity of the robot, the fastest time the robot could move from the starting position to the handover location was four seconds. This was the duration used for all motion models.

Another important aspect of the robot’s motion is the handover location, the position at which the robot finishes its reaching motion. Some researchers have used adaptive controllers which adjust for the position of the receiver’s hand, while others use a fixed position [Moon et al., 2014]. We chose to utilize a fixed position; however, the handover location was allowed to vary randomly around this fixed position by up to $\pm 3$ centimeters in all three axes. This slight variation in the end position was added to minimize the chances that the receiver would memorize and anticipate the handover location after they became familiar with the system.

#### 4.3 Independent Variable

We utilized a single independent variable, which was the reaching motion used by the robot.

Four different motions were used:

- Minimum Jerk (MJ)
- Decoupled Minimum Jerk (DMJ)
- Slanted Decoupled Minimum Jerk (SDMJ)
- Elliptical (E)

The order that each participant experienced the conditions was counterbalanced to alleviate possible ordering effects.

#### 4.4 Objects

For each condition, the participants received three objects (water bottle, vitamin bottle, and cube) from the robot, as shown in Fig. 3. Given that the experiment focuses purely on the motion of the handover trajectory, the starting position of each object was fixed relative to the robot base. The external forces and torques on the end effector were utilized to detect when the receiver had grasped the object.

#### 4.5 Participant Allocation

We recruited 32 participants (20 male and 12 female) aged from 19 – 28 (M=22.7, SD=2.09). The partici-

---

1This study has been approved by the Monash University Human Research Ethics Committee (Application ID: 27499)
pants were not compensated for their time. Seven of the participants had previously worked with robotics, two of the participants had completed similar studies, while the rest of the participants reported either not seeing a robot or only seeing commercially available robots.

4.6 Procedure
The study was conducted in a university laboratory, with an experimenter supervising the experiment. Upon arrival, participants were provided an explanatory statement to read and a consent form to sign. They then completed a demographic survey. Next, the experiment was outlined to the participant, and they then completed three practice handovers with the robot. During practice, the handover motion used by the robot for each handover was randomly selected, with no motion being used for more than one practice handover.

Participants were instructed to start each handover with their reaching hand by their side. The participant was then required to complete 12 successful handovers with the robot. After each condition, the participant completed a survey regarding their experience with that condition before moving to the next. At the end of all of the conditions, the user completed an additional post-experiment survey where they compared each of the conditions and had the opportunity to provide additional comments.

4.7 Objective Metrics
Four objective measures were recorded and analyzed during this study: (1) the percentage of successful handovers, (2) the start time of the human reach (Reach Time), (3) the middle time of reach (Middle Time), and (4) the time that the robot’s gripper begins to release the object (Release Time). Each objective metric is defined more precisely below, and all time-based metrics are measured from when the robot starts the reaching motion. The Reach and Middle times were calculated from the recorded OAK-D videos of each handover. We used color segmentation techniques to determine the location of the participant’s hand at each step.

1. Success: The percentage of handovers which were successful.
2. Reach Time: The time at which the receiver begins to move their hand towards the object to grab it.
3. Middle Time: The time at which the receivers hand crosses a fixed pixel location as they move towards the object. This position was fixed for all participants, and represented the half-way position in pixel space, between the object transfer point and where the human was standing.
4. Release Time: The time at which the robot begins to release the object from the gripper.

All time metrics were measured in seconds. We included the Reach Time and Middle Time metrics due to the discovery made by [Moon et al. 2014] that there was no difference in Release Time for different gaze behavior in object handovers, but there was a significant difference in Reach Time. Therefore, we have included an additional metric, Middle Time, to investigate whether there are significant differences in the reaction times across the entire motion of the receiver during the handover.

4.8 Subjective Metrics
After each condition, participants were asked a series of questions to establish which handover motion they subjectively preferred. Additionally, according to the recommendations made by [Ortenzi et al. 2021], we included several questions to evaluate the fluency of the interaction, trust, and working alliance of the human-robot interaction. All questions were asked on a 7-point Likert scale. The participants’ questions are listed in Table 1.

| Table 1: User Study Survey Questions. |
|---------------------------------------|
| Human-Robot Fluency                   |
| Q1: The human-robot team worked fluently together |
| Q2: The robot contributed to the fluency of the interaction |
| Trust in Robot                        |
| Q3: I trusted the robot to do the right thing at the right time |
| Q4: The robot was trustworthy         |
| Safety                                |
| Q5: I felt safe during the handover   |
| Predictability                        |
| Q6: I understand what the robot’s goals are |
| Q7: The robot and I are working towards mutually agreed upon goals |
| Natural Motion                        |
| Q8: The motion was natural            |
| Q9: The motion was human-like         |
| Q10: I was comfortable with the handover motion |

After participants completed all four conditions, they were asked which condition they preferred and whether they perceived any differences between the conditions, with the option to provide written feedback.

5 Results
5.1 Objective Metrics
Out of the 385 handovers completed, only one handover was classified as failing. The participant took the object with their left hand rather than their right hand, re-attempting this handover immediately afterward. This produced a success rate of 99.7%.
The results for the remaining objective metrics are shown in Table 2. We conducted a one-way ANOVA analysis with a significance level of $\alpha = 0.05$, which revealed no significant differences in the three time-based metrics.

5.2 Subjective Metrics

The survey results are shown in Fig. 4. A one-way ANOVA was conducted on the Likert scale subjective questions, returning no significant difference between the conditions for any of the ten questions. The statistics for
Table 2: Objective metric results. We observe no significant difference between any of the trajectories for the objective metrics. E, DMJ, MJ, SDMJ represent Elliptical, Decoupled Minimum Jerk, Minimum Jerk, and Slanted Decoupled Minimum Jerk, respectively. Bold numbers indicate the motion/s with the lowest mean time value (in seconds) for each objective metric.

|       | E   | DMJ | MJ  | SDMJ |
|-------|-----|-----|-----|------|
|       | μ   | σ   | μ   | σ   | μ   | σ   | μ   | σ   | F(1,63) | p     |
| Reach Time | 4.28 | 0.59 | 4.15 | 0.49 | 4.15 | 0.56 | 4.27 | 0.57 | 0.53 | 0.66 |
| Middle Time | 5.02 | 0.55 | 4.96 | 0.48 | 4.95 | 0.50 | 5.03 | 0.48 | 0.20 | 0.90 |
| Release Time | 5.95 | 0.55 | 5.87 | 0.73 | 5.89 | 0.72 | 5.84 | 0.53 | 0.15 | 0.93 |

Table 3: User Responses to the Survey Questions shown in Table 1. E, DMJ, MJ, SDMJ represent Elliptical, Decoupled Minimum Jerk, Minimum Jerk, and Slanted Decoupled Minimum Jerk, respectively. Bold numbers indicate the motion/s with the highest mean for each question.

|       | E   | DMJ | MJ  | SDMJ |
|-------|-----|-----|-----|------|
|       | μ   | σ   | μ   | σ   | μ   | σ   | μ   | σ   | F(1,63) | p     |
| Q1    | 6.16 | 0.72 | 6.09 | 0.86 | 6.03 | 0.78 | 6.00 | 0.76 | 0.25 | 0.86 |
| Q2    | 5.84 | 0.88 | 5.88 | 0.98 | 5.97 | 1.09 | 5.94 | 0.80 | 0.12 | 0.95 |
| Q3    | 6.09 | 0.82 | 6.13 | 0.91 | 6.19 | 0.78 | 6.19 | 0.78 | 0.10 | 0.96 |
| Q4    | 6.31 | 0.82 | 6.22 | 0.91 | 6.38 | 0.71 | 6.28 | 0.81 | 0.20 | 0.89 |
| Q5    | 6.44 | 0.76 | 6.44 | 0.91 | 6.53 | 0.67 | 6.59 | 0.67 | 0.33 | 0.81 |
| Q6    | 6.41 | 0.76 | 6.22 | 1.04 | 6.25 | 1.05 | 6.31 | 0.82 | 0.26 | 0.86 |
| Q7    | 6.28 | 0.89 | 6.19 | 1.03 | 6.28 | 0.92 | 6.25 | 0.88 | 0.07 | 0.97 |
| Q8    | 5.31 | 1.12 | 5.25 | 1.39 | 5.31 | 1.15 | 5.38 | 0.98 | 0.06 | 0.98 |
| Q9    | 4.53 | 1.32 | 4.44 | 1.41 | 4.50 | 1.41 | 4.59 | 1.32 | 0.07 | 0.97 |
| Q10   | 6.28 | 0.73 | 5.97 | 1.18 | 6.31 | 0.59 | 6.16 | 0.77 | 1.09 | 0.36 |

these questions are summarised in Table 3. Participants commonly mentioned that they could not perceive any difference between the conditions.

6 Discussion

Our results show no significant difference between any of the motion models in our task for any subjective or objective metrics measured, indicating that participants could not perceive significant differences. Many participants also indicated in their verbal responses that they could not identify changes in the robot motion between conditions. A couple of participants could determine that there were two planes on which the end-effector moved (one for DMJ and MJ and another for E and SDMJ), but they could not tell the difference between the two motions that traveled on each plane.

An interesting observation was the substantially lower average scores (across all motions) for two of the subjective Likert questions compared to the rest. The lower-scored questions were “The motion was human-like” (Q9) and “The motion was natural” (Q8), which both aimed to determine which motion the participants perceived as more human-like. The lower average scores for these two questions compared to the rest may indicate that participants did not consider any of the motions very human-like.

The highest scoring question (Q5) was in relation to safety, which suggests that users felt comfortable with the robotic platform and the robot’s motions. This is likely due to the speed of the robot and the reliability of our system to perform handovers. “The robot was trustworthy” (Q4) and “I understand what the robot’s goals are” (Q6) were also rated highly, suggesting that the users were trusting of the robot and understood the robot’s goals.

A factor that may explain our results is the configuration of our robotic platform, which can be seen in Fig. 1. Common robotic platforms, including the Franka Emika Panda robotic arm used in our experiments, tend not to be very human-like when mounted in a tabletop configuration. Using a more human-like platform, such as a humanoid robot or a horizontally-mounted robotic configuration [Pan et al., 2019b] could help humans perceive the motions as more natural or human-like. Furthermore, we only consider the trajectory of the end-effector.

However, efficiently configuring the robot arm coordinated joint trajectories to closely match human whole arm configurations while respecting the kinematics of the manipulator could help users perceive the motion in a more human-like manner. Additionally, the robot joints move quite rapidly near the start of the handover motion to ensure the end-effector follows the required path, which may distract the participant from observing the robot’s exact handover motion more closely.
These results also indicate that the handover motion utilized on non-humanoid robotic systems may not be consequential to successfully perform object handovers. Participants subjectively rated all four conditions highly for fluency, comfort, trustworthiness, working alliance and safety, indicating that whilst the handover motions were not that well perceived as human-like or natural, they were satisfied with their interactions with the robot. We think it would be valuable to perform the same study again, however, varying the handover scenarios by changing the object transfer point, human position, and arm speed. This could help expose the differences between the trajectories to the users and expose a stronger need for legible motions.

7 Conclusion and Future Work

We compared the subjective perception of different trajectories on robot-to-human handovers. For the trajectories tested, all of which were selected for their human-inspired nature, our results did not find significant differences in successful robot-to-human handover interactions. This finding is in contrast to an earlier hypothesis on human-to-human object handovers [Sheikholeslami et al., 2018] which posited that the elliptical model would enable more fluent and efficient object handovers as compared to the other human-like motion models.

An obvious extension of this work is to investigate the effect of the other factors on the subjective perception of humans, such as the robot speed and a varying object transfer point of a handover. Future research can also examine the effect of combining human-like trajectories with additional explicit communication methods, such as gaze [Moon et al., 2014], speech [Chao and Thomaz, 2010], gestures [Kwan et al., 2020] and augmented reality markers [Newbury et al., 2022]. The motion of the robot base, in addition to the robotic arm, can also be considered [He et al., 2022]. Furthermore, we believe looking at the effect of the subjective perception of human-like trajectories on human-to-robot handovers [Rosenberger et al., 2021], [Yang et al., 2021] could help provide exciting insights. Another interesting research avenue is investigating whether the conclusions reached for robot-to-human handovers are also valid for human-to-robot handovers.

References

[Admoni et al., 2014] Henny Admoni, Anca Dragan, Siddhartha S Srinivasa, and Brian Scassellati. Deliberate delays during robot-to-human handovers improve compliance with gaze communication. In Human-Robot Interaction, 2014.

[Bestick et al., 2018] Aaron Bestick, Ravi Pandya, Ruzena Bajcsy, and Anca D. Dragan. Learning human ergonomic preferences for handovers. In 2018 IEEE International Conference on Robotics and Automation (ICRA), pages 3257–3264, 2018.

[Cakmak et al., 2011] Maya Cakmak, Siddhartha S Srinivasa, Min Kyung Lee, Sara Kiesler, and Jodi Forlizzi. Using spatial and temporal contrast for fluent robot-human hand-overs. In HRI, page 489–496, 2011.

[Chan et al., 2020] Wesley P. Chan, Matthew K. X. J. Pan, Elizabeth A. Croft, and Masayuki Inaba. An affordance and distance minimization based method for computing object orientations for robot human handovers. IJSR, 12(1), 2020.

[Chan et al., 2021] Wesley P. Chan, Tin Tran, Sara Sheikholeslami, and Elizabeth Croft. An experimental validation and comparison of reaching motion models for unconstrained handovers: Towards generating humanlike motions for human-robot handovers. In Humanoids, 2021.

[Chao and Thomaz, 2010] Crystal Chao and Andrew Lockerd Thomaz. Turn taking for human-robot interaction. In 2010 AAAI Fall Symposium Series, 2010.

[Dragan et al., 2013] Anca D. Dragan, Kenton C.T. Lee, and Siddhartha S. Srinivasa. Legibility and predictability of robot motion. In 2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI), pages 301–308, 2013.

[Glasauer et al., 2010] S. Glasauer, M. Huber, P. Basili, A. Knoll, and T. Brandt. Interacting in time and space: Investigating human-human and human-robot joint action. In RO-MAN, 2010.

[Grigore et al., 2013] Elena Corina Grigore, Kerstin Eder, Anthony G Pipe, Chris Melhuish, and Ute Leonards. Joint action understanding improves robot-to-human object handover. In IROS, 2013.

[He et al., 2022] Kerry He, Pradeepsundar Simini, Wesley P Chan, Dana Kulić, Elizabeth Croft, and Akansel Cosgun. On-the-go robot-to-human handovers with a mobile manipulator. In IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), 2022.

[Hogan, 1982] Neville Hogan. Control and coordination of voluntary arm movements. In ACC, page 522–528, 1982.

[Huber et al., 2008] Markus Huber, Markus Rickert, Alois Knoll, Thomas Brandt, and Stefan Glasauer. Human-robot interaction in handing-over tasks. In RO-MAN, page 107–112, 2008.
[Huber et al., 2009] Markus Huber, Helmuth Radrich, Cornelia Wendt, Markus Rickert, Alois Knoll, Thomas Brandt, and Stefan Glasauer. Evaluation of a novel biologically inspired trajectory generator in human-robot interaction. In RO-MAN, page 639–644, 2009.

[Kwan et al., 2020] Jun Kwan, Chinkye Tan, and Akansel Cosgun. Gesture recognition for initiating human-to-robot handovers. In RO-MAN Workshop in Active Vision and Perception in Human-Robot Collaboration, 2020.

[Kyrarini et al., 2021] Maria Kyrarini, Fotios Lygerakis, Akilesh Rajavenkatanarayanan, Christos Sevastopoulos, Harish Ram Nambiappan, Kodur Krishna Chaitanya, Ashwin Ramesh Babu, Joanne Mathew, and Fillia Makedon. A survey of robots in healthcare. Technologies, 2021.

[Moon et al., 2014] AJung Moon, Daniel M. Troniak, Brian Gleeson, Matthew K.X.J. Pan, Minhua Zeng, Benjamin A. Blumer, Karon MacLean, and Elizabeth A. Croft. Meet me where i’m gazing: how shared attention gaze affects human-robot handover timing. In HRI, 2014.

[Newbury et al., 2022] Rhys Newbury, Akansel Cosgun, Tysha Crowley-Davis, Wesley P. Chan, Tom Drummond, and Elizabeth Croft. Visualizing robot intent for object handovers with augmented reality. In IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), 2022.

[Ortenzi et al., 2021] Valerio Ortenzi, Akansel Cosgun, Tommaso Pardi, Wesley P Chan, Elizabeth Croft, and Dana Kulić. Object handovers: a review for robotics. IEEE Transactions on Robotics, 37(6):1855–1873, 2021.

[Pan et al., 2018] Matthew K.X.J. Pan, Elizabeth A Croft, and Günter Niemeyer. Exploration of geometry and forces occurring within human-to-robot handovers. In IEEE Haptics Symposium (HAPTICS), 2018.

[Pan et al., 2019a] Matthew K.X.J. Pan, Espen Knoop, Moritz Bächer, and Günter Niemeyer. Fast handovers with a robot character: Small sensorimotor delays improve perceived qualities. In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019.

[Pan et al., 2019b] Matthew K.X.J. Pan, Espen Knoop, Moritz Bächer, and Günter Niemeyer. Fast handovers with a robot character: Small sensorimotor delays improve perceived qualities. In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019.

[Portugal et al., 2015] David Portugal, Luis Santos, Paulo Alvito, Jorge Dias, George Samaras, and Eleni Christodoulou. Socialrobot: An interactive mobile robot for elderly home care. In IEEE/SICE International Symposium on System Integration (SII), 2015.

[Robotics Australia Group, 2022] Robotics Australia Group. A robotics roadmap for australia 2022, 2022.

[Rosenberger et al., 2021] Patrick Rosenberger, Akansel Cosgun, Rhys Newbury, Jun Kwan, Valerio Ortenzi, Peter Corke, and Manfred Grafinger. Object-independent human-to-robot handovers using real time robotic vision. IEEE Robotics and Automation Letters, 2021.

[Sheikholeslami et al., 2018] S. Sheikholeslami, Gilwoo Lee, J. Hart, S. Srinivasa, and E. Croft. A study of reaching motions for collaborative human-robot interaction. In ISER, 2018.

[Shibata et al., 1997] Satoru Shibata, Benlamine Mohamed Sahbi, Kanya Tanaka, and Akira Shimizu. An analysis of the process of handing over an object and its application to robot motions. In SMC, 1997.

[Strabala et al., 2013] Kyle Strabala, Min Kyung Lee, Anca Dragan, Jodi Forlizzi, Siddhartha S Srinivasa, Maya Cakmak, and Vincenzo Micelli. Towards seamless human-robot handovers. Journal of Human-Robot Interaction, 1(1):1–23, 2013.

[Tan et al., 2009] Jeffrey Too Chuan Tan, Feng Duan, Ye Zhang, Kei Watanabe, Ryu Kato, and Tamio Arai. Human-robot collaboration in cellular manufacturing: Design and development. In IROS, 2009.

[Yang et al., 2021] Wei Yang, Chris Paxton, Arsalan Mousavian, Yu-Wei Chao, Maya Cakmak, and Dieter Fox. Reactive human-to-robot handovers of arbitrary objects. In IEEE International Conference on Robotics and Automation (ICRA), 2021.

[Zheng et al., 2015] Minhua Zheng, AJung Moon, Elizabeth A. Croft, and Max Q.-H. Meng. Impacts of robot head gaze on robot-to-human handovers. International Journal of Social Robotics, 7(5):783–798, 11 2015.

[Zhou and Dragan, 2018] Allan Zhou and Anca D. Dragan. Cost functions for robot motion style. In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018.