

Influence of Perceived Danger on Proxemics in Human-Robot Object Handovers

Carl Oechsner
LMU Munich
Munich, Germany
carl.oechsner@ifi.lmu.de

Jan Leusmann
LMU Munich
Munich, Germany
jan.leusmann@ifi.lmu.de

Robin Welsch
Aalto University
Aalto, Finland
robin.welsch@aalto.fi

Andreas Martin Butz
LMU Munich
Munich, Germany
butz@ifi.lmu.de

Sven Mayer
LMU Munich
Munich, Germany
TU Dortmund University
Dortmund, Germany
info@sven-mayer.com

Abstract

As robots increasingly share human environments, we need to understand how their behavioral parameters affect our perceptions of safety and interaction quality. To explore this, we conducted a user study (N=48) investigating the relationship between approach speed, stopping distance, and the perceived danger of the object itself in a robot-human handover situation. Participants iteratively adjusted the speed and distance of a robot handing them items of varying danger categories to find a combination they considered optimal. We found a significant impact of the delivered item's perceived danger index on speed and distance preferences and could identify a linear dependency. By eliciting user preferences for these parameters, we can provide guidelines for adaptable robotic interactions that are considered safe, thus contributing to the design of spaces where robots and humans can coexist seamlessly, emphasizing user experience, trust, and effective collaboration.

CCS Concepts

• Human-centered computing; • Computer systems organization → Robotics;

Keywords

Robotics, Kinematics and Dynamics, Social Robots, Proxemics, Human-Robot Collaboration

ACM Reference Format:

Carl Oechsner, Jan Leusmann, Robin Welsch, Andreas Martin Butz, and Sven Mayer. 2025. Influence of Perceived Danger on Proxemics in Human-Robot Object Handovers. In *Mensch und Computer 2025 (MuC '25)*, August 31-September 03, 2025, Chemnitz, Germany. ACM, New York, NY, USA, 10 pages. <https://doi.org/10.1145/3743049.3743064>

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

MuC '25, Chemnitz, Germany

© 2025 Copyright held by the owner/author(s).

ACM ISBN 979-8-4007-1582-2/25/08

<https://doi.org/10.1145/3743049.3743064>



Figure 1: We investigate the preferred speed and distance when handing over objects varying in perceived danger.

1 Introduction

With recent advances in Human-Robot Interaction (HRI), collaborative robots (cobots) will likely interact closely with humans in smart spaces in the near future. They will not only handle the physical tasks we assign them, but instead, humans and robots can be expected to achieve goals collaboratively. Especially in domestic settings, cobots are claimed to provide a variety of advantages and opportunities [48, 54, 66]. However, robotic smart spaces, where robots perform tasks in close proximity to humans, require a thoughtful design of the spatial interaction parameters. One key factor for the successful adoption of robot technology is user trust, which has been shown to rely, among other factors, on robots respecting spatial norms similar to those among humans. Therefore, the spatial rules of social interaction (proxemics) are a key challenge of human-aware navigation in robotics, especially during handovers, one of the most fundamental tasks in human-robot collaboration. Research suggests that the objects involved in a situation influence the assessment of potential hazards and the user's perception of adequate distance and speed [65], which in turn directly affects trust. While holistic approaches exist to accommodate user trust in human-robot handovers, the interplay between proxemics and the objects involved in handovers has, to our knowledge, not yet been investigated systematically.

Designing interaction with robots in shared spaces requires careful consideration of how this space is used. Much like in human-human interaction [21, 22, 59], where we maintain a safe and comfortable distance to protect our bodies from others [28], people keep a certain distance when interacting with robots [26, 41, 51, 56]. Although studies have mapped out the immediate protective space, the peripersonal space (PPS) [26, 50, 56] and spaces for social interaction [41, 51] around the robot itself, proxemic studies have not yet considered cobots that assist users with tools [15]. If a cobot is carrying a knife, how should it approach the user, and what distance and speed should it observe? We know that collaborative settings in which robots hold objects can vary in perceived danger level [43] and that perceived danger affects proxemic variables such as the perception of time-to-contact [7] and the PPS [12, 31, 50]. Thus, we must investigate how objects of different perceived danger held by a cobot will affect spatial interaction in terms of speed and distance [19] in order to make HRI in handover tasks feel safe [57].

We conducted a within-subjects study (N=48) to investigate the effects of the object in a handover situation on proxemic variables (desired distance and speed) of the robot approach (see Figure 1). For this, we used a 6 DoF robot arm on a linear track to approach the user and hand over different objects. We asked participants to iteratively set the approaching speed and stopping distance to let them find the settings they felt most comfortable with. This was done for nine different objects and three baseline measurements.

We found that the perceived danger of an object has a significant influence on the preferred approach speed and stopping distance during handovers. Furthermore, we could model a linear dependency of both speed and distance on an object's perceived danger index (PDI), a score representing its perceived dangerousness [42]. HRI researchers and designers aiming to create or investigate collaborative scenarios can use our findings to inform initial robot configurations. More specifically, kinetic parameters with which the user will feel safe during handovers can be systematically derived from the PDI of an item. This allows system designers to create robotic systems that align with user expectations and enhance the user experience in smart spaces.

2 Related Work

Understanding the foundational principles of proxemics among humans provides the baseline for investigating how people expect and interpret the spatial behavior of robots around them. This chapter reviews existing research on proxemics, approach behaviors, and object danger perception to establish the foundation for our study.

2.1 Approach Distance

Human-Human Proxemics. First introduced by Hall [22], the term *Proxemics* describes the phenomenon of individuals maintaining varying distances based on social context, relationship, and cultural norms. He categorized the space around a person into concentric circular zones: intimate (<45cm), personal (<120cm), social (<305cm), and public [21]. The Personal Space (PS) denotes the area around a person in which an intruding person can cause discomfort and arousal [24]. Since then, the concept of PS, its size and shape, as well as influencing factors, have undergone continuous refinement.

A widely acknowledged strategy for investigating PS is the stop-distance approach pioneered by Williams [74], where the distance to the subject is gradually altered until the distance at which the subject first becomes uncomfortable. The size of this range is influenced by a variety of factors, such as culture and behavior of the other person [1, 2], social status [18, 40, 63], personality [16, 64, 74], motivation [28], level of stress [14], or height [10].

The term "Interpersonal Distance" (IPD) denotes the actual distance an individual keeps during an interaction, and the preferred IPD is commonly considered to lie within the boundary of PS. According to Argyle's equilibrium theory [4], a person's preferred IPD is the point within the PS where an individual's desire to approach (e.g., to converse) and to avoid (e.g., unwanted intimacy) are balanced. Iachini et al. [32] found different values for participants when approaching vs. being approached in the stop-distance task; however, Welsch et al. [72] could not replicate this. Instead, they discovered that the increase in discomfort due to deviations from the preferred IPD varies depending on whether the actual motion is directed toward or away from the subject.

PPS is a concept that is relevant when discussing human spatial behavior. Unlike PS, rooted in psychology and social sciences, PPS is defined in neuroscience and refers to the immediate area surrounding the body where objects can be directly reached and manipulated [33]. It plays a crucial role in motor control by guiding actions such as reaching, grasping, and avoiding obstacles through continuous remapping of the multisensory space around the body based on sensorimotor requirements [8]. Hunley and Lourenco [31] note that many of the mechanisms and measures used to define PPS are quite similar to those for PS. Iachini et al. [32] found that values for PS and PPS differed only in the passive approach, concluding that PPS and PS coincide in the active approach.

Human-Robot Proxemics. Extending from Hall [22], proxemics in the context of HRI is the study of what influences the preferred distance between human and robot [49]. To establish trust in human-robot relationships and to successfully integrate robots into social spaces, they must adhere to the same social movement norms as humans [6, 49]. Like in human proxemics, the stop-distance task is a widely used approach to investigate comfortable distances between humans and robots [61, 70]. However, findings on PS in human-robot scenarios vary greatly. While several studies found that human-robot IPDs do not differ from those among humans [30, 69], others find much larger distances (e.g., 173cm while standing [68]) or smaller (e.g., 30cm [67]) distances than Hall's boundaries from 45 to 120cm [22]. Sorrentino et al. [60] argue that a robot's appearance and personality traits can influence proxemic behavior, indicating that robots might need to adopt unique strategies that differ from those expected in human-human interactions.

Syrdal et al. [64] recognized the effect of user personality. However, they state the difference seems to disappear over time, which was later confirmed [39, 46]. The varying results can be explained by the varying study contexts (i.e., user task, approach direction), different types of robots, and individual preferences and experiences. Torta et al. [68] propose a model for PS robotic navigation, taking into account contextual factors such as user position or personal preferences, suggesting specific distances that robots should observe to ensure user comfort.

The range of factors influencing PS shows that special attention should be given to the parameters during user studies. To isolate the effect of a specific variable in user studies, it is crucial to control or minimize other factors known to impact user perception and comfort. Additionally, factors that vary based on user personality traits, such as sensitivity to speed, proximity, or perceived anthropomorphism, should be standardized to settings that are least likely to cause discomfort, ensuring that observed effects are primarily attributable to the variable under investigation.

2.2 Approach Velocity

The robot movement speed can influence an interaction's perceived safety and its overall effectiveness. The scenarios most investigated in prior work involve the robot passing the participant or approaching them for the purpose of interaction. For passing tasks, speed and distance interplay to shape user perceptions. For example, Neggers et al. [52] tested various robot speeds (35, 80, 125, 170 cm/s) at different distances (60, 80, 100, 120 cm), finding that the closest distance required the slowest speed for user comfort, while the most comfortable speed at all other distances was 80 cm/s. The discomfort associated with the slowest speed was attributed to increased waiting times during the interaction. Similarly, Klüber and Onnasch [36] demonstrated a tradeoff between speed and distance in virtual reality (VR); they observed that participants allowed the robot to come closer when it moved at slower speeds, suggesting a balancing act between speed and distance for safety and comfort. Zhang et al. [77] reported similar tradeoffs in mixed reality.

For approach tasks involving direct interaction, user comfort levels are influenced by the purpose of the robot's approach and the associated velocity. Askin and Bitsch [5] found that a robot approaching at a moderate speed (34.4 cm/s) was preferred over slower (17.9 cm/s) or faster speeds (51.1 cm/s) during an assembly task, where a robot placed screws, indicating that high speeds can lead to discomfort. Lu et al. [45] compared side and front approaches at two velocities (50 and 100 cm/s) and found that stress and mental demand were higher at the faster speed, particularly during side approaches, highlighting the effect of approach direction on user perceptions. Koppenborg et al. [37] found that a robot velocity of 140 cm/s significantly increased workload, anxiety, and risk cognition compared to a velocity of 75 cm/s. Slajpah et al. [58] came to a similar conclusion and further identified that participants rated higher arousal and lower safety for the faster speed (80 cm/s), especially when standing compared to sitting. They suggested a differential threshold for noticeable speed changes of around 25-30%. There is also work on dynamic approaches. For example, Mitsunaga et al. [47] proposed a strategy where the robot adapts its speed to subconscious human body signals, aiming to enhance user comfort by synchronizing its behavior with subtle human cues.

In summary, existing studies provide inconsistent recommendations regarding safe or acceptable robot approach speeds in collaborative settings, leaving developers and researchers without clear design guidelines, a shortcoming which is also criticized by Koppenborg et al. [37]. However, the influencing factors seem to be approach direction and trajectory predictability. Furthermore, there seems to be a tradeoff between speed and approach distance, i.e., the robot can come closer if it runs slower.

2.3 Handovers

Prior research in psychology established that the item(s) involved influence the assessment of the danger of a situation. Tabor et al. [65] found that a person's distance from an object that might evoke pain is generally estimated too low. Participants significantly underestimated the distance to the pain-evoking stimulus compared to a pain-relieving stimulus. Cole et al. [11] observed the same phenomenon after comparing participants' assumptions about their distance to a threatening animal; they found that the reported levels of threat and disgust significantly affected their estimation, i.e., objects are perceived closer than they are. While those studies examined conditions in which both participant and object were static, Brendel et al. [7] investigated the difference in the estimated time of collision between threatening and non-threatening objects on a collision course with the participant. A stereoscopic display showed objects of varying danger approaching, and participants were to indicate the probable moment of collision. Results show that this moment was significantly earlier for dangerous objects than for neutral ones. Witt and Sugovic [76] confirmed that the moving speed of objects perceived as dangerous is rated significantly higher than that of neutral items. They show that the perceived threat by an object influences how its speed and distance are assessed, namely that its speed is overestimated and its distance is underestimated. Since a dangerous item can potentially inflict harm or injury, these responses make evolutionary sense, giving a person more time and room to take protective measures.

However, a systematic assessment of how the object affects the user is missing from most studies that investigate the interaction between speed, distance, and object in handover tasks. Anelli et al. [3] established a "danger rating" prior to investigating resonant mechanisms during interaction with objects of varying danger. Leusmann et al. [43] established a database of household objects associated with users' PDI, a value indicating whether an item is perceived as dangerous on a scale from 0 (strongly disagree) to 100 (strongly agree) when handled by a robot, allowing HRI researchers to correlate observations to objects involved during collaboration.

3 Studying Preferred Robot Speed and Distance for Different Objects

Building on this understanding of human-human and human-robot proxemics, our study investigates the interplay of three critical factors – preferred working speed, preferred distance, and perceived item danger – on HRI dynamics. Specifically, we aim to answer the following research questions:

RQ1. How does the perceived danger index of an object influence preferred approach *a)* speed and stopping *b)* distance in robot-to-human handovers?

RQ2. How does the perceived danger index influence the ability to predict preferred approach *a)* speed and *b)* stopping distance in robot-human handovers?

We selected a range of items for the robot to carry from the database by Leusmann et al. [43]. We divided their PDI (range: 0-100) into three equal parts (0-33 = Low, 33-66 = Medium, 66-100 = High) and selected three objects from each (see Table 1). Finally,

we added three control conditions in which the robot approached with an empty gripper, i.e., without carrying any object. These served as a baseline for comparison to understand the impact of item danger on preferred approach parameters. Alongside the nine item conditions, this resulted in a total of 12 conditions, this resulted in a total of 12 conditions, the order of which was determined using a size 12 Latin-square design to account for habituation effects.

Most studies on trust or discomfort during HRI presented discrete variations of robot dynamics and collected participant responses through surveys. However, for our specific goal of modeling continuous user preferences for approach speed and distance, we sought a more fine-grained, interactive method. Surveys often rely on retrospective reflection and require pausing the task [27]. By contrast, our iterative method allowed participants to adjust robot behavior in situ, better capturing their immediate comfort preferences. Furthermore, investigating discrete levels often results in missing the true optimum, which usually falls between two adjacent levels. Even more granular levels can only approximate optimal values while increasing complexity. In this work, we aim to understand the relationship among the three continuous variables: speed, distance, and object danger. In a full-design study with 3-5 levels each, this would result in an unfeasible number of iterations. Thus, we decided to fix only one variable and let participants actively set values for approach velocity and stopping distance before triggering the robot approach (see Figure 2 for the study setup). They were asked to repeat this procedure until they found the combination of speed and distance they felt most comfortable with. This procedure allowed us to gather in-situ quantitative data representing participants' optimal comfort levels.

3.1 Study Environment

We conducted the study in a laboratory that was carefully modified to resemble a home environment. The laboratory featured a functional custom-made kitchen, including appliances and a vinyl floor with a hardwood look, creating a setting that closely mimics the aesthetics and functionality of a real home. This setup contrasts with the environments used in many other proxemics studies, which are often conducted in sterile laboratories, seminar rooms, or VR simulations. While those also provide controlled conditions, they often

Table 1: Selected items with their PDI according to Leumann et al. [43] on a 0-100 scale and their respective category.

Item	PDI	Danger Category
Sponge	7.4	Low
Measuring Cup	13.8	
Funnel	18.4	
Coffee Cup	34.7	Medium
Plate	36.7	
Bottle	39.3	
Scissors	67.2	High
Carving Fork	68.3	
Chef's Knife	70.8	



Figure 2: Close-up of the study setup. Participants stand at one of two approach positions facing the robot arm. When the robot stops moving, participants can press the green button to confirm the end of the handover.

lack ecological validity, making it difficult to generalize findings to real-world home environments. By replicating a realistic domestic setting, our study ensures that the insights gained are more directly applicable to the design of robots for actual households, thereby bridging the gap between controlled experimental research and practical, real-world applications (see Figure 2).

3.2 Apparatus

The robot used in the study is an overhead, rail-mounted Kinova Gen3 6DoF robotic arm [34] operated via Kortex Python API [55] v2.6.0. For the study, the robot picks and places items from the countertop using a RobotiQ 2F-140 [35] gripper. During the approach, the end-effector moves at a constant height toward the participant. The robot base is attached to a carriage unit moving at a height of 2.31m along a rail (aligning with the gripper movement). The unit can extend downwards by 40cm, extending the robot's reach, which was used to adapt to the participant's height. Both carriage motions are driven by 24V servo motors, controlled by an Elmo Gold Duo digital servo drive [44]. Participants could control the robot using a web interface shown on an Android tablet, featuring a start button and two unlabeled sliders for the speed and distance settings. The slider for setting distance was labeled "Closeness" to map more extreme values consistently to the right. The sliders are mapped linearly to values in $v_{app} = [44, 76] \frac{cm}{s}$ or $d_{app} = [120, 0] cm$ respectively. A desktop computer opposing the kitchenette was used for surveys and communication with the investigator.

3.3 Pilot Study

In a pilot experiment, we ran trials where the robot approached participants without an item to determine the available speed range. Following the staircase method [20], we determined a mean threshold of $\bar{v} = 66 \frac{cm}{s}$ ($SD = 11$) above which participants considered the approach too fast. The available speed range was then set to the maximum possible speed of $v_{max} = 76 \frac{cm}{s}$ and $v_{min} = \bar{v} - (v_{max} - \bar{v}) - SD = 0.44 \frac{cm}{s}$. For the stopping distance range, we allowed participants to choose from the whole range of 0-120cm defined as PS by Hall [21].

3.4 Procedure

After welcoming the participants, we explained the study procedure to them (see Figure 3). After all open questions were answered, we

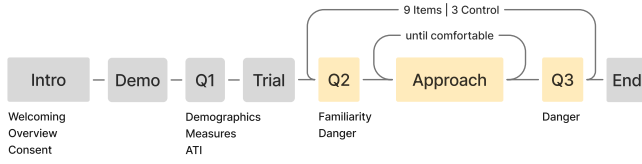


Figure 3: Study Procedure. In the main part (yellow), participants were presented with 9 items or control conditions (outer loop) and could repeat the approach until they felt comfortable with the selected speed and distance (inner loop).

asked them to sign an informed consent form. Our ethics board approved the study. Afterward, we showed them the robot approach procedure and how to use the control interface. During this session, we showed two approaches with values for speed and distance from the middle of the available range. Participants were also informed that the robot’s closest possible stopping point corresponded approximately to the location of their sternum, providing a clear reference for the minimum distance. Before they continued, we asked them to fill out a demographic survey and the Affinity of Technology (ATI) questionnaire [17], and we measured their body height to adapt handover height (Q1). We then explained the apparatus to them and let them try it out with a neutral item before proceeding with the main part of the study, with 12 conditions. We asked participants to evaluate each approach as if they were working in the kitchen and requested the robot to bring the item.

After this, the study conductor left the room to help participants put themselves into this situation and to avoid any bias on participant behavior, emotion, or performance [38, 53]. The study conductor observed the running study via video stream and could communicate with participants via an audio interface if needed. For safety reasons, the study conductor could intervene or stop the study in case of any issues in the study room. Each condition started with participants filling out a survey assessing the upcoming item regarding familiarity and perceived hazardousness (Q2). Then, the iterative approach section began with the robot repeatedly approaching the participant with the same item but with different speeds and distances as defined by the user. The slider’s initial values for each condition were at 50%. In subsequent repetitions during the condition, participants were presented with their last input to be adjusted. An iteration followed these steps: (1) At the approach position facing the robot, participants indicate on a tablet that they are ready, and the robot moves to the starting point 180 cm away from them. (2) Participants set speed and distance on a tablet and start the approach. (3) The robot moves at the set speed and stops at the set distance. The robot moved with its gripper moving in a straight line at a constant height of 71% of the participant’s body height [23, 75] (see Figure 4). The robot’s trajectory was kept constant throughout the study to exclude a lack of predictability as an influential factor [37]. We chose the gripping position for each object in a manner that allowed participants to easily grasp them [62], e.g., knife, scissors, and fork were held by the robot in such a way that the handle was pointing towards the participant. (4) Instead of taking the item, participants simulated the handover by pushing a button attached to the robot’s last joint. This way,

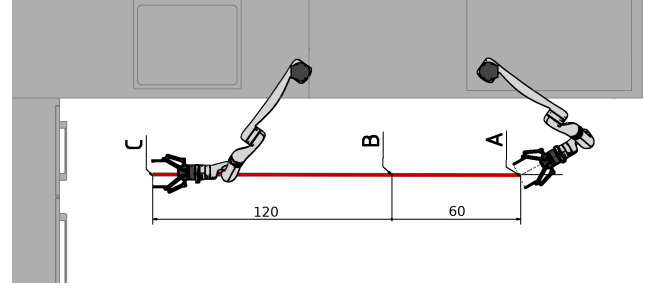


Figure 4: Schematic top-down view of a robot approach to position 1. For position 2, the procedure is mirrored (see Figure 2). The participant stands at position (C), facing point (A), the robot’s starting position (depicted by the right robot). Point (B) marks the Personal Space boundary [21]. Based on the participant’s selection for the closeness of approach $s \in [0, 1]$, the stopping position is $d_{app} = \vec{AB} + s \cdot \vec{BC}$. The left robot depicts the stopping position for $s = 1$.

the presentation of an item was kept constant for each approach. This concludes an iteration, and the participant moves to the opposite approach position in order to minimize unnecessary and time-consuming robot motion back to the original position.

We asked participants to iterate until they felt comfortable with the robot’s approach speed and stopping distance. In this case, they tapped a button on the tablet and went to answer a final question assessing the danger perceived by the robot’s approach in the last condition (Q3). After participants had completed all scenarios, we thanked them for their participation and reimbursed them.

3.5 Participants

We recruited 48 participants via the institution’s mailing list between the ages of 16 and 71 ($M = 29.2$, $SD = 11.1$), of which 29 were female and 19 were male. Most (19) of them had never encountered robots before, 18 between one and three times, five between four and seven times, and five more than seven times, most of whom reported their experience with vacuum robots. To adapt handover height, we measured their body height before the experiment ($M = 1.73m$, $SD = 0.09m$). We also asked them about their living situation, specifically the number of people in their household and the number of times they prepared meals per week together with others, to evaluate their customization to sharing the kitchen space. Participants had an average ATI [17] of 3.84 ($SD = 0.83$). 23% of our participants lived alone, 31% with one other person, and 46% with two or more. 19% of participants reported no joint cooking, 31% on average once per week, 19% twice per week, and 31% at least three times per week ($M = 2.35times$, $SD = 2.32$).

4 Results

We analyzed the impact of item DANGER on preferred approach SPEED and stopping DISTANCE and derived direct relationships between the variables that allow us to predict robot motion parameters based on the carried item.

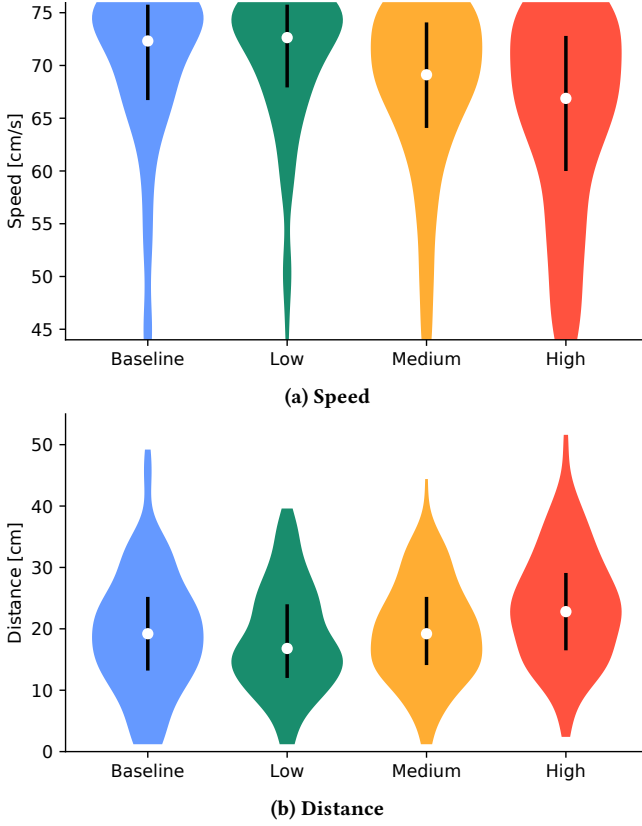


Figure 5: Measured values for the optimal speed and distance for the four danger categories.

4.1 Impact on Speed (RQ1a)

We investigated the impact of the objects' DANGER on the selected movement SPEED. We first performed a Shapiro-Wilk Normality Test, which showed that the data is not normally distributed ($W = .871, p < .001$). Thus, we performed a Friedman test, which showed a significant effect of danger on speed ($\chi^2(48) = 44.6, p < .001$, Kendall $W = .31$, see Figure 5a). Finally, we conducted Wilcoxon signed rank post hoc comparisons. We found statistically significant differences for *Baseline* vs. *High* ($p < .001$), *Low* vs. *High* ($p < .001$), *Medium* vs. *High* ($p < .001$), *Baseline* vs. *Medium* ($p = .042$), and *Low* vs. *Medium* ($p < .002$); all other $p > .05$.

4.2 Impact on Distance (RQ1b)

We investigated the impact of the objects' DANGER on the selected DISTANCE. We first performed a Shapiro-Wilk Normality Test, which showed that the data is not normally distributed ($W = .984, p = .025$). Thus, we performed a Friedman test, which showed a significant effect of danger on distance ($\chi^2(48) = 28.6, p < .001$, Kendall $W = .199$, see Figure 5b). Finally, we conducted Wilcoxon signed rank post hoc comparisons. We found statistically significant differences for *Baseline* vs. *High* ($p < .001$), *Low* vs. *High* ($p < .001$), and *Medium* vs. *High* ($p < .001$); all other $p > .05$.

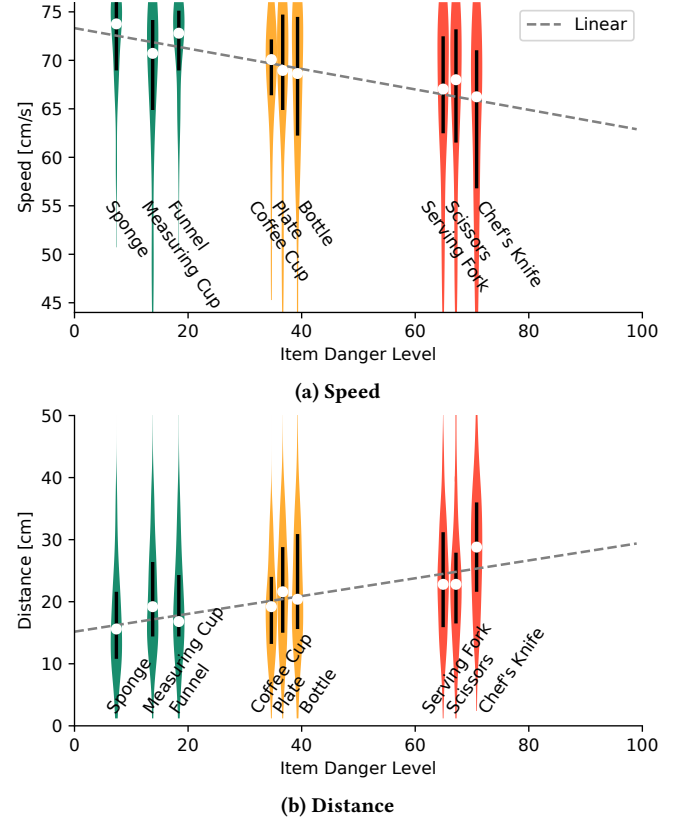


Figure 6: Linear model to predict the users' preferred approach dynamics given the objects' danger level.

4.3 Modeling Impact on Distance & Speed (RQ2)

Since we saw an overall impact of DANGER on both SPEED and DISTANCE, we modeled their impact using the perceived danger values from Leusmann et al. [43]. We found that linear models result in the best fits, i.e., the lowest AIC, with $R^2 = .83$ for speed (see Figure 6a) and $R^2 = .77$ for distance (see Figure 6b). Thus, we can model the maximum speed with $v_{app}(d)$ with

$$v_{app}(d) = -0.105 * d + 73.321 \quad (1)$$

and the distance $dist_{app}(d)$ with

$$dist_{app}(d) = 0.144 * d + 15.171 \quad (2)$$

where d is the PDI of the object.

Next, we investigated the relationship between SPEED and DISTANCE. For this, we estimated the probability density function, i.e., the likelihood of a given combination being picked by the users, using a kernel density estimation (see Figure 7). With this, we understand which combination of speed and distance is generally most likely for each condition. We marked the maxima for each condition in Figure 7, which shows that the more dangerous the object is, the higher the distance and the lower the speed. This is unsurprising as the independent findings (see Figure 5) show a similar outcome. However, this also means that a speed-distance tradeoff did not manifest. We also investigated the gradient from the most likely

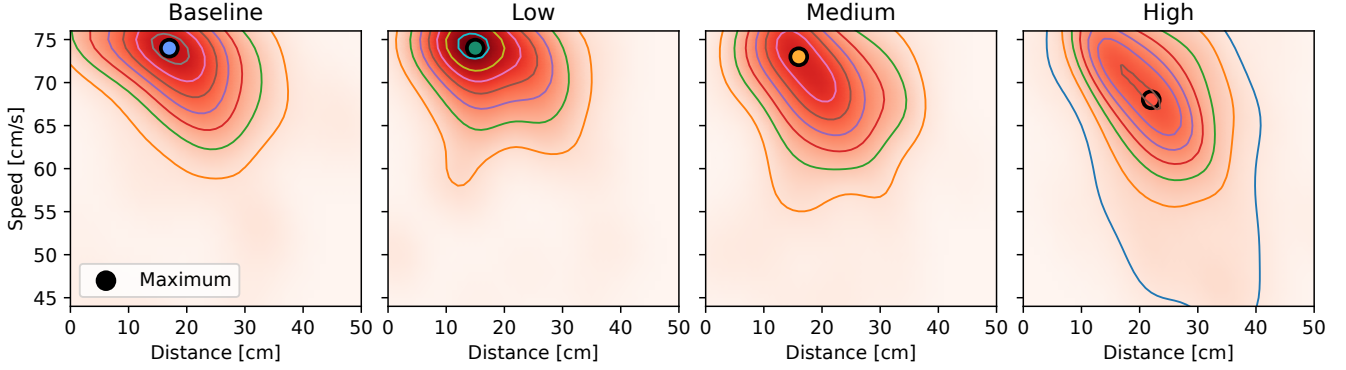


Figure 7: Heatmap of the probability density distribution of DISTANCE and SPEED. Darker red areas show more responses and, thus, more agreement. A trend is visible from the maximum to the bottom right, indicating that more dangerous items elicit both larger preferred distances and lower preferred speeds. The maximum speed we could explore was limited by local legal requirements about safe moving speeds for robots.

combination (maximum) to the least likely (see Figure 7). From this, we see that the widest distances between the contour lines occur in the direction of larger distances and slower speeds, indicating the direction of a higher probability of a combination.

5 Discussion

First, we will address our research questions. Then, we will discuss broader implications for the design of cobots, including practical recommendations for adaptive behaviors and considerations for integrating robots into shared human environments. Finally, we address the limitations of the study and propose future research to extend these insights to more diverse and complex contexts.

5.1 Higher Object Danger Leads to Slower Preferred Speeds and Higher Preferred Distances

We investigated preferences for distance and speed in a cobot handover situation with items of varying PDI. Participants preferred a slower approach speed for objects perceived as dangerous, such as a chef’s knife, while faster approaches were preferred for handovers with less dangerous objects, such as a sponge. We found the reverse pattern with regard to preferred distance, where items with higher danger levels were associated with larger preferred distances for handovers. Thus, for RQ1, our findings indicate that an item’s perceived danger significantly influences both the preferred robot speed and the desired stopping distance.

5.2 Linear Relationship

We identified a linear relationship between an item’s PDI d and the user-preferred approach speed v_{app} and stopping distance $dist_{app}$. Our findings are relatively in line with the values from the large-scale online study [43]. This suggests that Equation 1 and 2 can be used for all 153 items from the online survey to find the optimally preferred speed and distance values for these objects. This is a direct response to our RQ2, as we could successfully develop linear models with a reasonably good fit for both speed and distance.

5.3 No Speed-Distance Tradeoff

In related work, some studies found a tradeoff between speed and distance (e.g., Klüber and Onnasch [36]), i.e., that closer stopping distances would require lower approach speeds. However, our study design did not provoke such behavior in any of the tested danger categories since we only manipulated one (danger) of the three variables: danger, speed, and distance. Hence, we cannot make a general statement about such an effect. Instead, our findings indicate that users prefer lower speeds and higher stopping distances simultaneously when delivering potentially hazardous items. We argue that our results reflect users’ preferred expectations for robot behavior rather than merely tolerated interactions. For the design of trustworthy robot interactions, this means that rather than compensating for closer approaches with slower approach speeds, greater distances and slower speeds should be maintained simultaneously when handling potentially hazardous items, so situations where a tradeoff would be needed can be avoided.

5.4 General Implications for Handover Tasks

Our findings underscore the importance of context-aware behavioral adaptations for human-aware navigation in HRI. This means that robots operating in spaces shared with humans should modulate their approach behavior as a function of the PDI of the objects they carry. Interestingly, we observed slightly greater stopping distances and slower approach speeds for the empty gripper condition (Baseline) than for the low-danger category. This can potentially be explained by the appearance of the open empty gripper, which multiple participants stated “looks a bit like it’s going to choke you.” One solution would be to move the gripper closed when empty.

Importantly, designing for acceptance and trust in both private and shared spaces requires focusing not just on what is technically possible but on what is comfortable for and preferred by users. We tailored our study to this goal by giving participants free choice to set the approach parameters they found most appropriate. This approach ensured that the findings reflect actual user preferences

rather than imposed tolerances. While we did not observe a speed-distance tradeoff, this does not disprove it. Instead, it indicates that users prefer to avoid situations where such a tradeoff would become necessary, particularly when dealing with hazardous items.

Beyond domestic settings, our findings can inform a range of applications in robotic spaces. For example, robots in healthcare settings could use similar adaptive behaviors when handing over medical tools or assisting with patient care. In industrial environments, robots could dynamically adjust their approach parameters to ensure worker safety and efficiency when handling potentially hazardous items. For instance, when transporting a dangerous chemical, even if technically entirely safe, robots should approach more slowly and stop at a greater distance to prioritize user comfort.

More generally, for proxemics research, our study confirms that object characteristics, such as their perceived danger, influence the desired distance and approach speed. Traditional proxemics often focus on the cultural [21], personal [25], social-context [71] or room characteristics [73] but have yet to combine agents with objects. Therefore, our research on cobots likely also extends and merges research on PPS regarding objects [9] and PS regarding agents [13], as both spaces are not deemed to be as distinct [31]. Objects and their characteristics consequently influence proxemic interactions and, therefore, should be considered in human-robot proxemics.

5.5 Limitations

We conducted our study in a laboratory equipped with a fully functional kitchen. While this offers higher ecological validity compared to a sterile lab or virtual environment, it remains a controlled laboratory setup. Real homes may contain more variability, clutter, or unstructured activity that could influence proxemic preferences and user responses in ways that this study does not capture.

We used a ceiling-mounted Kinova Gen3 6DoF arm, which is representative of a wide range of robotic manipulators. However, the results may not generalize to robots with different forms, degrees of anthropomorphism, or motion characteristics. It needs to be investigated how our results extend to different robot characteristics or multi-arm robots in general. Moreover, different approach trajectories, arm shapes, or motion smoothness could influence perceived safety and comfort in handovers. Further studies with alternative robotic morphologies are needed to explore this. Here, it might also be relevant to see how danger levels add up across agents in space, e.g., whether multiple cobots carrying dangerous objects lower speed and increase distance in a multiplicative fashion.

Participants performed the task in a focused, distraction-free context. While this allowed us to isolate the effects of perceived object danger, it does not reflect common user behavior in actual kitchen use. In reality, users might divide their attention across multiple tasks and prioritize fluency or rely more on peripheral cues, potentially affecting their sensitivity to robot proximity or motion. To establish approach profiles with higher ecological validity, future work should investigate how attention, task load, and situational awareness influence proxemic preferences during handovers, for which the values discovered in our study can serve as the baseline.

While grasping the item was entirely possible within our study setup, we have not analyzed the user's hand movement kinematics

or hesitation during the handover. We carefully designed the procedure to control for item presentation and interaction variability. This decision allowed for cleaner comparison of approach behavior but omits potentially valuable behavioral data that could reflect trust or readiness. Future studies should record and analyze human grasping behavior, which could provide further information in terms of hesitancy to initiate a handover with the cobot and could potentially be used to adapt interaction. Future research may want to look at the behavioral grasping parameters of the user in a dedicated study that also controls for object orientation, for instance, as a function of approach speed.

We saw that participants tolerated a relatively high approach speed for the cobot, especially for the Low and Medium categories. Future studies might explore wider or adaptive speed ranges to investigate where these thresholds truly lie. However, this may need more extended safety procedures than those already strictly employed in our study. While participants were not shown the full speed range directly, the preparatory session allowed them to observe and test several speed settings. Still, not all may have encountered the full behavioral range of the robot, especially the minimum velocity, which may have influenced their internal reference points when adjusting the approach parameters. The ceiling effect could be further attributed to the high predictability of the robot's trajectory. However, to maintain consistency in assessing the impact of object danger, the trajectory shape was kept constant. Investigating the influence of trajectory predictability in combination with varying danger levels, as well as potential learning and habituation effects, is another valuable direction for future research. Future studies may circumvent this limitation by presenting a set of distances and speeds and asking participants for their comfort level [72] or measuring physiological responses typically present when PS is violated, e.g., a rise in electrodermal activity [29]. The increase in trials necessary for our research questions would have rendered the study impractical.

Our participants ($M = 29.2$, $SD = 11.1$) were rather young, with 75% of participants being 33 years or younger, and the majority held a university degree (79% with Bachelor's or higher). This may limit the generalizability of our findings to older or less formally educated populations. The participants' ATI score of 3.84 ($SD = 0.84$) is near average (3.5 Franke et al. [17]), suggesting a relatively neutral attitude toward technology. However, we did not analyse a potential effect on proxemic preferences. Future studies should examine whether such factors influence preferred speed and distance.

6 Conclusion

As robots will increasingly enter human living spaces and collaborate with humans, they need to adhere to human rules of social behavior, in particular regarding their usage of space. We identified a lack of holistic evaluations of human-robot proxemics concerning the perceived danger of the objects they handle. To close this gap, we conducted a user study ($N=48$) centered around a robot handover situation with items of varying levels of perceived danger. We found that higher perceived danger of an object consistently resulted in slower preferred movement speeds and larger preferred stopping distances. These preferred values for speed and distance can be modeled as linear functions of the PDI with a reasonably good fit.

These insights can help to develop adaptive robotic systems that can maintain a good user experience in different interaction contexts. Designers can also create customizable interaction settings and provide a starting point for users to personalize their experiences with robotic systems. Additionally, this knowledge is valuable for education and training in HRI design since it emphasizes the importance of adapting interactions to user perceptions. In robotic smart spaces, such as kitchens or healthcare facilities, our findings can guide the design of systems where robots seamlessly share human environments. By respecting spatial norms and adjusting behaviors based on context, these systems can enhance the perception of safety, efficiency, and overall user experience. Future work should explore how these principles scale to multi-robot environments and dynamic, multi-user settings.

Open Science

We provide all anonymized measurements from the study and the Python and R analysis scripts in the supplementary material and on the Open Science Framework: <https://osf.io/v3ypb>.

Acknowledgments

This project is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 425412993 and is part of Priority Program SPP2199 Scalable Interaction Paradigms for Pervasive Computing Environments.

References

- [1] Cheryl Albas. 1991. Proxemic Behavior: A Study of Extrusion. *Journal of Social Psychology* 131, 5 (Oct. 1991), 697–702. doi:10.1080/00224545.1991.9924653
- [2] Cheryl Albas and Daniel Albas. 1989. Aligning Actions: The Case of Subcultural Proxemics - ProQuest. *Canadian Ethnic Studies, Calgary* 21, 2 (1989), 74–83.
- [3] Filomena Anelli, Anna M. Borghi, and Roberto Nicoletti. 2012. Grasping the Pain: Motor Resonance with Dangerous Affordances. *Consciousness and Cognition* 21, 4 (Dec. 2012), 1627–1639. doi:10.1016/j.concog.2012.09.001
- [4] Michael Argyle and Janet Dean. 1965. Eye-Contact, Distance and Affiliation. *Sociometry* 28, 3 (Sept. 1965), 289. doi:10.2307/2786027 jstor:2786027
- [5] Jeremy Askin and Günter Bitsch. 2023. Investigating the Influence of a Cobot's Average Tool Center Point Speed on Human Work Behavior in a Cooperative Human-Robot Collaboration Assembly Station. *Procedia CIRP* 118 (2023), 217–222. doi:10.1016/j.procir.2023.06.038
- [6] Christopher Brandl, Alexander Mertens, and Christopher M. Schlick. 2016. Human-Robot Interaction in Assisted Personal Services: Factors Influencing Distances That Humans Will Accept between Themselves and an Approaching Service Robot: Human-Robot Interaction in Assisted Personal Services. *Human Factors and Ergonomics in Manufacturing & Service Industries* 26, 6 (Nov. 2016), 713–727. doi:10.1002/hfm.20675
- [7] Esther Brendel, Patricia R. DeLucia, Heiko Hecht, Ryan L. Stacy, and Jeff T. Larsen. 2012. Threatening Pictures Induce Shortened Time-to-Contact Estimates. *Attention, Perception, & Psychophysics* 74, 5 (July 2012), 979–987. doi:10.3758/s13414-012-0285-0
- [8] C. Brozzoli, L. Cardinali, F. Pavani, and A. Farnè. 2010. Action-Specific Remapping of Peripersonal Space. *Neuropsychologia* 48, 3 (Feb. 2010), 796–802. doi:10.1016/j.neuropsychologia.2009.10.009
- [9] R. J. Bufacchi. 2017. Approaching Threatening Stimuli Cause an Expansion of Defensive Peripersonal Space. *Journal of Neurophysiology* 118, 4 (Oct. 2017), 1927–1930. doi:10.1152/jn.00316.2017
- [10] Marc E. Caplan and Morton Goldman. 1981. Personal Space Violations as A Function of Height. *The Journal of Social Psychology* 114, 2 (Aug. 1981), 167–171. doi:10.1080/00224545.1981.9922746
- [11] Shana Cole, Emily Balcettis, and David Dunning. 2013. Affective Signals of Threat Increase Perceived Proximity. *Psychological Science* 24, 1 (Jan. 2013), 34–40. doi:10.1177/0956797612446953
- [12] Alyanne M. De Haan, Miranda Smit, Stefan Van Der Stigchel, and H. Chris Dijkerman. 2016. Approaching Threat Modulates Visuotactile Interactions in Peripersonal Space. *Experimental Brain Research* 234, 7 (July 2016), 1875–1884. doi:10.1007/s00221-016-4571-2
- [13] Martin Johannes Dechant, Robin Welsch, Julian Frommel, and Regan L. Mandryk. 2022. (Don't) Stand by Me: How Trait Psychopathy and NPC Emotion Influence Player Perceptions, Verbal Responses, and Movement Behaviours in a Gaming Task. In *CHI Conference on Human Factors in Computing Systems*. ACM, New Orleans LA USA, 1–17. doi:10.1145/3491102.3502014
- [14] Michael A. Dosey and Murray Meisels. 1969. Personal Space and Self-Protection. *Journal of Personality and Social Psychology* 11, 2 (1969), 93–97. doi:10.1037/h0027040
- [15] Haonan Duan, Yifan Yang, Daheng Li, and Peng Wang. 2024. Human-Robot Object Handover: Recent Progress and Future Direction. *Biomimetic Intelligence and Robotics* 4, 1 (March 2024), 100145. doi:10.1016/j.birob.2024.100145
- [16] Lorraine Eastwood. 1985. Personality, Intelligence and Personal Space among Violent and Non-Violent Delinquents. *Personality and Individual Differences* 6, 6 (Jan. 1985), 717–723. doi:10.1016/0191-8869(85)90082-0
- [17] Thomas Franke, Christiane Attig, and Daniel Wessel. 2019. A Personal Resource for Technology Interaction: Development and Validation of the Affinity for Technology Interaction (ATI) Scale. *International Journal of Human-Computer Interaction* 35, 6 (April 2019), 456–467. doi:10.1080/10447318.2018.1456150
- [18] Dair L. Gillespie and Ann Leffler. 1983. Theories of Nonverbal Behavior: A Critical Review of Proxemics Research. *Sociological Theory* 1 (1983), 120–154. <http://www.jstor.org/stable/202049>
- [19] Saul Greenberg, Nicolai Marquardt, Till Ballendat, Rob Diaz-Marino, and Miaosen Wang. 2011. Proxemic interactions: the new ubicomp? *interactions* 18, 1 (2011), 42–50.
- [20] Wang Hailing. 2024. Staircase Method. In *The ECPH Encyclopedia of Psychology*. Springer Nature Singapore, Singapore, 1–2. doi:10.1007/978-981-99-6000-2_861-1
- [21] Edward Twitchell Hall. 1966. *The hidden dimension* (anchor books, 1990 ed.). Doubleday, New York.
- [22] Edward T. Hall, Ray L. Birdwhistell, Bernhard Bock, Paul Bohannon, A. Richard Diebold, Marshall Durbin, Munro S. Edmonson, J. L. Fischer, Dell Hymes, Solon T. Kimball, Weston La Barre, J. E. McClellan, Donald S. Marshall, G. B. Milner, Harvey B. Sables, George L. Trager, and Andrew P. Vayda. 1968. Proxemics [and Comments and Replies]. *Current Anthropology* 9, 2/3 (April 1968), 83–108. doi:10.1086/200975
- [23] Clint Hansen, Paula Arambel, Khalil Ben Mansour, Véronique Perdereau, and Frédéric Marin. 2017. Human-Human Handover Tasks and How Distance and Object Mass Matter. *Perceptual and Motor Skills* 124, 1 (Feb. 2017), 182–199. doi:10.1177/0031512516682668
- [24] Leslie A. Hayduk. 1978. Personal Space: An Evaluative and Orienting Overview. *Psychological Bulletin* 85, 1 (Jan. 1978), 117–134. doi:10.1037/0033-2909.85.1.117
- [25] Leslie A. Hayduk. 1981. The Shape of Personal Space: An Experimental Investigation. *Canadian Journal of Behavioural Science / Revue canadienne des sciences du comportement* 13, 1 (Jan. 1981), 87–93. doi:10.1037/h0081114
- [26] Patrick Holthaus and Sven Wachsmuth. 2012. Active Peripersonal Space for More Intuitive HRI. In *2012 12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*. IEEE, Osaka, Japan, 508–513. doi:10.1109/HUMANOIDS.2012.6651567
- [27] Sarah K. Hopko, Yinsu Zhang, Aakash Yadav, Prabhakar R. Pagilla, and Ranjana K. Mehta. 2024. Brain-Behavior Relationships of Trust in Shared Space Human-Robot Collaboration. *ACM Transactions on Human-Robot Interaction* 13, 1 (March 2024), 1–23. doi:10.1145/3632149
- [28] Mardi J. Horowitz. 1964. Body-Buffer Zone. *Archives of General Psychiatry* 11, 6 (Dec. 1964), 651. doi:10.1001/archpsyc.1964.01720300081010
- [29] Ann Huang, Pascal Knierim, Francesco Chiossi, Lewis L. Chuang, and Robin Welsch. 2022. Proxemics for Human-Agent Interaction in Augmented Reality. In *CHI Conference on Human Factors in Computing Systems*. ACM, New Orleans LA USA, 1–13. doi:10.1145/3491102.3517593
- [30] Helge Huettenrauch, Kerstin Eklundh, Anders Green, and Elin Topp. 2006. Investigating Spatial Relationships in Human-Robot Interaction. In *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, Beijing, China, 5052–5059. doi:10.1109/IROS.2006.282535
- [31] Samuel B. Hunley and Stella F. Lourenco. 2018. What Is Peripersonal Space? An Examination of Unresolved Empirical Issues and Emerging Findings. *WIREs Cognitive Science* 9, 6 (Nov. 2018), e1472. doi:10.1002/wcs.1472
- [32] Tina Iachini, Yann Coello, Francesca Frassinetti, and Gennaro Ruggiero. 2014. Body Space in Social Interactions: A Comparison of Reaching and Comfort Distance in Immersive Virtual Reality. *PLoS ONE* 9, 11 (Nov. 2014), e111511. doi:10.1371/journal.pone.0111511
- [33] Tina Iachini, Stefano Pagliaro, and Gennaro Ruggiero. 2015. Near or Far? It Depends on My Impression: Moral Information and Spatial Behavior in Virtual Interactions. *Acta Psychologica* 161 (Oct. 2015), 131–136. doi:10.1016/j.actpsy.2015.09.003
- [34] Kinova inc. 2024. Discover our Gen3 robots | Kinova — kinovarobotics.com. <https://www.kinovarobotics.com/product/gen3-robots>. [Accessed 15-01-2025].
- [35] Robotiq inc. 2025. Adaptive Grippers | Robotiq — robotiq.com. <https://robotiq.com/products/adaptive-grippers#Two-Finger-Gripper>. [Accessed 15-01-2025].

- [36] Kim Klüber and Linda Onnasch. 2023. Keep Your Distance! Assessing Proxemics to Virtual Robots by Caregivers. In *Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*. ACM, Stockholm Sweden, 193–197. doi:10.1145/3568294.3580070
- [37] Markus Koppenborg, Peter Nickel, Birgit Naber, Andy Lungfiel, and Michael Huelke. 2017. Effects of Movement Speed and Predictability in Human–Robot Collaboration. *Human Factors and Ergonomics in Manufacturing & Service Industries* 27, 4 (July 2017), 197–209. doi:10.1002/hfm.20703
- [38] Angela R. Lebbon and John Austin. 2013. A Preliminary Examination of the Effects of Observer Presence on Work-Related Behavior in a Simulated Office. *Journal of Organizational Behavior Management* 33, 3 (Sept. 2013), 185–199. doi:10.1080/01608061.2013.815095
- [39] Kheng Lee Koay, Dag Sverre Syrdal, Michael L. Walters, and Kerstin Dautenhahn. 2007. Living with Robots: Investigating the Habituation Effect in Participants' Preferences During a Longitudinal Human-Robot Interaction Study. In *RO-MAN 2007 - The 16th IEEE International Symposium on Robot and Human Interactive Communication*. IEEE, Jeju, South Korea, 564–569. doi:10.1109/ROMAN.2007.4415149
- [40] Ann Leffler, Dair L. Gillespie, and Joseph C. Conaty. 1982. The Effects of Status Differentiation on Nonverbal Behavior. *Social Psychology Quarterly* 45, 3 (1982), 153–161. doi:10.2307/3033648 jstor:3033648
- [41] Benedikt Leichtmann and Verena Nitsch. 2020. How Much Distance Do Humans Keep toward Robots? Literature Review, Meta-Analysis, and Theoretical Considerations on Personal Space in Human-Robot Interaction. *Journal of Environmental Psychology* 68 (April 2020), 101386. doi:10.1016/j.jenvp.2019.101386
- [42] Jan Leusmann. 2023. HRI Objects — hri-objects.leusmann.io. <https://hri-objects.leusmann.io/>. [Accessed 15-01-2025].
- [43] Jan Leusmann, Carl Oechsner, Johanna Prinz, Robin Welsch, and Sven Mayer. 2023. A Database for Kitchen Objects: Investigating Danger Perception in the Context of Human-Robot Interaction. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI EA '23). Association for Computing Machinery, New York, NY, USA, Article 6, 9 pages. doi:10.1145/3544549.3585884
- [44] Elmo Motion Control Ltd. 2025. The Gold Duo is a two axis wall-mounted and compact servo drive — elmomc.com. <https://www.elmomc.com/product/gold-duo/>. [Accessed 15-01-2025].
- [45] Lu Lu, Ziyang Xie, Hanwen Wang, Bingyi Su, and Xu Xu Edward P. Fitts. 2022. Assessing Workers' Mental Stress in Hand-over Activities during Human-robot Collaboration. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 66, 1 (Sept. 2022), 537–541. doi:10.1177/1071181322661194
- [46] Ross Mead and Maja Mataric. 2016. Robots Have Needs Too: How and Why People Adapt Their Proxemic Behavior to Improve Robot Social Signal Understanding. *Journal of Human-Robot Interaction* 5, 2 (Sept. 2016), 48. doi:10.5898/JHRI.5.2.Mead
- [47] N. Mitsunaga, C. Smith, T. Kanda, H. Ishiguro, and N. Hagita. 2008. Adapting Robot Behavior for Human–Robot Interaction. *IEEE Transactions on Robotics* 24, 4 (Aug. 2008), 911–916. doi:10.1109/TRO.2008.926867
- [48] Elias Montini, Fabio Daniele, Lorenzo Agbomemewa, Matteo Confalonieri, Vincenzo Cutrona, Andrea Bettoni, Paolo Rocco, and Andrea Ferrario. 2024. Collaborative Robotics: A Survey From Literature and Practitioners Perspectives. *Journal of Intelligent & Robotic Systems* 110, 3 (Aug. 2024), 117. doi:10.1007/s10846-024-02141-z
- [49] Jonathan Mumm and Bilge Mutlu. 2011. Human-Robot Proxemics: Physical and Psychological Distancing in Human-Robot Interaction. In *Proceedings of the 6th International Conference on Human-robot Interaction*. ACM, Lausanne Switzerland, 331–338. doi:10.1145/1957656.1957786
- [50] Magda Mustile, Anna M. Borghi, Davide De Tommaso, and Agnieszka Wykowska. 2024. The Defensive Role of the Peripersonal Space in Social Contexts. doi:10.31234/osf.io/rbdgc
- [51] Margot M. E. Neggers, Raymond H. Cuijpers, and Peter A. M. Ruijten. 2018. Comfortable Passing Distances for Robots. In *Social Robotics*, Shuzhi Sam Ge, John-John Cabibihan, Miguel A. Salichs, Elizabeth Broadbent, Hongsheng He, Alan R. Wagner, and Álvaro Castro-González (Eds.), Vol. 11357. Springer International Publishing, Cham, 431–440. doi:10.1007/978-3-030-05204-1_42
- [52] Margot M. E. Neggers, Raymond H. Cuijpers, Peter A. M. Ruijten, and Wijnand A. Ijsselstein. 2022. The Effect of Robot Speed on Comfortable Passing Distances. *Frontiers in Robotics and AI* 9 (July 2022), 915972. doi:10.3389/frobt.2022.915972
- [53] Austin Lee Nichols and Jon K. Maner. 2008. The Good-Subject Effect: Investigating Participant Demand Characteristics. *The Journal of General Psychology* 135, 2 (April 2008), 151–166. doi:10.3200/GENP.135.2.151-166
- [54] Carl Oechsner, Sven Mayer, and Andreas Butz. 2022. Challenges and Opportunities of Cooperative Robots as Cooking Appliances. *Proceedings of the Workshop on Engaging with Automation* 3154 (April 2022).
- [55] Kinova Robotics. 2024. GitHub - Kinovarobotics/Kinova-kortex2_Gen3_G3L: Code examples and API documentation for KINOVA® KORTX™ robotic arms — github.com. https://github.com/Kinovarobotics/Kinova-kortex2_Gen3_G3L. [Accessed 15-01-2025].
- [56] Alessandro Roncone, Matej Hoffmann, Ugo Pattacini, Luciano Fadiga, and Giorgio Metta. 2016. Peripersonal Space and Margin of Safety around the Body: Learning Visuo-Tactile Associations in a Humanoid Robot with Artificial Skin. *PLOS ONE* 11, 10 (Oct. 2016), e0163713. doi:10.1371/journal.pone.0163713
- [57] Behzad Sadrfaridpour and Yue Wang. 2018. Collaborative Assembly in Hybrid Manufacturing Cells: An Integrated Framework for Human–Robot Interaction. *IEEE Transactions on Automation Science and Engineering* 15, 3 (July 2018), 1178–1192. doi:10.1109/TASE.2017.2748386
- [58] Sebastjan Slajpah, Kristina Rakinic, Kristina Nikolovska, Luka Komidar, Anja Podlesek, Gaja Zager Kocjan, Marko Munih, and Matjaz Mihelj. 2021. Effect of Speed, Speed Differences, and Motion Type on Perceived Safety of Collaborative Robots. In *2021 20th International Conference on Advanced Robotics (ICAR)*. IEEE, Ljubljana, Slovenia, 1036–1041. doi:10.1109/ICAR53236.2021.9659479
- [59] Robert Sommer. 1959. Studies in Personal Space. *Sociometry* 22, 3 (Sept. 1959), 247. doi:10.2307/2785668 jstor:2785668
- [60] A. Sorrentino, O. Khalid, L. Coviello, F. Cavallo, and L. Fiorini. 2021. Modeling Human-like Robot Personalities as a Key to Foster Socially Aware Navigation. In *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*. IEEE, Vancouver, BC, Canada, 95–101. doi:10.1109/RO-MAN50785.2021.9515556
- [61] Jessi Stark, Roberta R.C. Mota, and Ehud Sharlin. 2018. Personal Space Intrusion in Human-Robot Collaboration. In *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*. ACM, Chicago IL USA, 245–246. doi:10.1145/3173386.3176998
- [62] Kyle Wayne Strabala, Min Kyung Lee, Anca Diana Dragan, Jodi Lee Forlizzi, Siddhartha Srinivasa, Maya Cakmak, and Vincenzo Micelli. 2013. Towards Seamless Human-Robot Handovers. *Journal of Human-Robot Interaction* 2, 1 (March 2013), 112–132. doi:10.5898/JHRI.2.1.Strabala
- [63] Lois O. Stratton, Dennis J. Tekippe, and Grad L. Flick. 1973. Personal Space and Self-Concept. *Sociometry* 36, 3 (Sept. 1973), 424. doi:10.2307/2786344 jstor:2786344
- [64] Dag Sverre Syrdal, Kheng Lee Koay, Michael L. Walters, and Kerstin Dautenhahn. 2007. A personalized robot companion? - The role of individual differences on spatial preferences in HRI scenarios. In *RO-MAN 2007 - The 16th IEEE International Symposium on Robot and Human Interactive Communication*. IEEE, Jeju, South Korea, 1143–1148. doi:10.1109/ROMAN.2007.4415252
- [65] Abby Tabor, Mark J. Catley, Simon C. Gandevia, Michael A. Thacker, Charles Spence, and G. L. Moseley. 2015. The Close Proximity of Threat: Altered Distance Perception in the Anticipation of Pain. *Frontiers in Psychology* 06 (May 2015). doi:10.3389/fpsyg.2015.00626
- [66] Claudio Taesi, Francesco Aggogeri, and Nicola Pellegrini. 2023. COBOT Applications—Recent Advances and Challenges. *Robotics* 12, 3 (June 2023), 79. doi:10.3390/robotics12030079
- [67] Leila Takayama and Caroline Pantofaru. 2009. Influences on Proxemic Behaviors in Human-Robot Interaction. In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, St. Louis, MO, USA, 5495–5502. doi:10.1109/IROS.2009.5354145
- [68] Elena Torta, Raymond H. Cuijpers, and James F. Juola. 2013. Design of a Parametric Model of Personal Space for Robotic Social Navigation. *International Journal of Social Robotics* 5, 3 (Aug. 2013), 357–365. doi:10.1007/s12369-013-0188-9
- [69] Michael L. Walters, Kerstin Dautenhahn, and Christopher L. Nehaniv. 2009. An Empirical Framework for Human-Robot Proxemics. In *Proceedings of New Frontiers in Human-Robot Interaction*. Society for the Study of Artificial Intelligence and the Simulation of Behaviour, Edinburgh, UK, 144–149.
- [70] Michael L. Walters, Mohammedreza A. Oskoei, Dag Sverre Syrdal, and Kerstin Dautenhahn. 2011. A Long-Term Human-Robot Proxemic Study. In *2011 RO-MAN*. IEEE, Atlanta, GA, USA, 137–142. doi:10.1109/ROMAN.2011.6005274
- [71] Robin Welsch, Heiko Hecht, and Christoph Von Castell. 2018. Psychopathy and the Regulation of Interpersonal Distance. *Clinical Psychological Science* 6, 6 (Nov. 2018), 835–847. doi:10.1177/2167702618788874
- [72] Robin Welsch, Christoph von Castell, and Heiko Hecht. 2019. The anisotropy of personal space. *PLOS ONE* 14, 6 (06 2019), 1–13. doi:10.1371/journal.pone.0217587
- [73] Michael J. White. 1975. Interpersonal Distance as Affected by Room Size, Status, and Sex. *The Journal of Social Psychology* 95, 2 (April 1975), 241–249. doi:10.1080/00224545.1975.9918710
- [74] John L. Williams. 1971. Personal Space and Its Relation to Extraversion-Introversion. *Canadian Journal of Behavioural Science / Revue canadienne des sciences du comportement* 3, 2 (April 1971), 156–160. doi:10.1037/h0082257
- [75] Bertram Coghlin Alan Windle. 1892. *The Proportions of the Human Body*. Baillière, Tindall and Cox, London, UK.
- [76] Jessica K. Witt and Mila Sugovic. 2013. Spiders Appear to Move Faster than Non-Threatening Objects Regardless of One's Ability to Block Them. *Acta Psychologica* 143, 3 (July 2013), 284–291. doi:10.1016/j.actpsy.2013.04.011
- [77] Jingxin Zhang, Omar Janeh, Nikolaos Katzakis, Dennis Krupke, and Frank Steinicke. 2019. Evaluation of Proxemics in Dynamic Interaction with a Mixed Reality Avatar Robot. *ICAT-EGVE 2019 - International Conference on Artificial Reality and Telexistence and Eurographics Symposium on Virtual Environments* (2019), 8 pages. doi:10.2312/EGVE.20191278