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

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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

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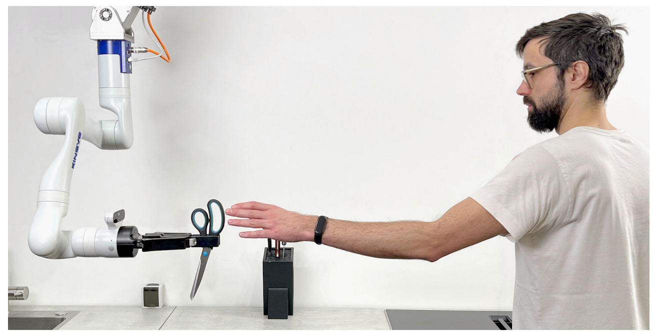


Figure 1: We investigate the preferred speed and distance when handing over objects varying in perceived danger.

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 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).

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

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

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 $\overline{v} = 66\frac{cm}{s}$ $(SD = 11)$ 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 $v_{min} = \overline{v} - (v_{max} - \overline{v}) - SD = 0.44\frac{cm}{s}$. 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

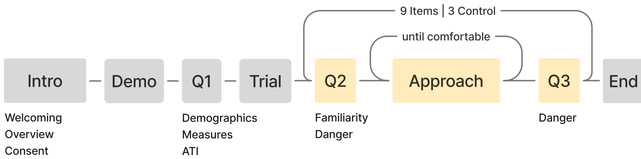


Figure 3: Study Procedure. In the main part (yellow), participants were presented with 9 items or control conditions (outer loop) and could repeat the approach until they felt comfortable with the selected speed and distance (inner loop).

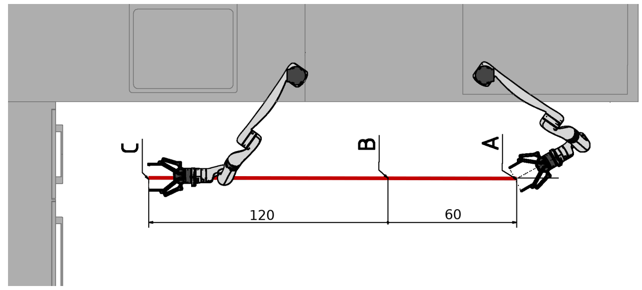


Figure 4: Schematic top-down view of a robot approach to position 1. For position 2, the procedure is mirrored (see Figure 2). The participant stands at position (C), facing point (A), the robot's starting position (depicted by the right robot). Point (B) marks the Personal Space boundary [21]. Based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

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, 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.

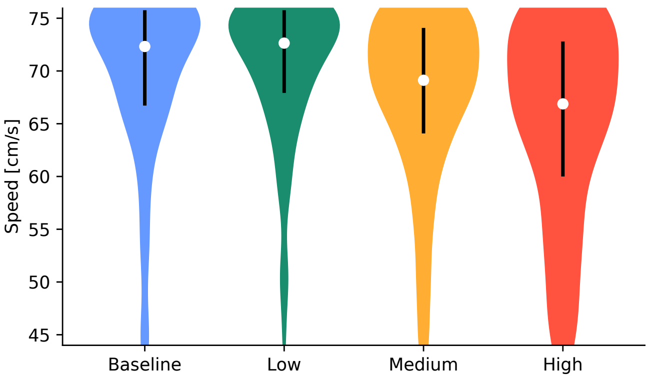
We asked participants to iterate until they felt comfortable with the robot's approach speed and stopping distance. In this case, they tapped a button on the tablet and went to answer a final question assessing the danger perceived by the robot's approach in the last condition (Q3). After participants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

3.5 Participants

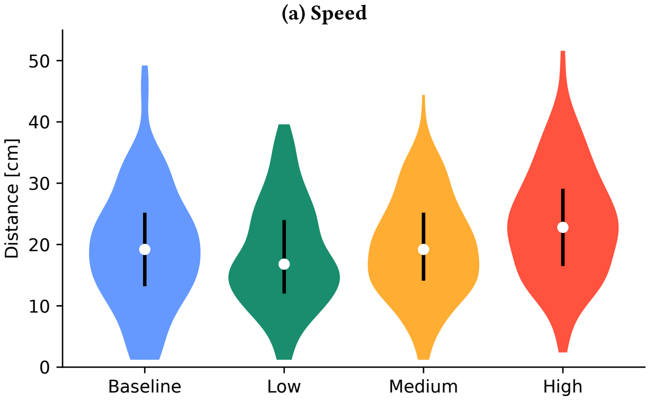
We recruited 48 participants via the institution's mailing list between the ages of 16 and 71 ($M = 29.2$, $SD = 11.1$), of which 29 were female and 19 were male. Most (19) of them had never encountered robots before, 18 between one and three times, five between four and seven times, and five more than 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 ($M = 2.35 times$, $SD = 2.32$).

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.

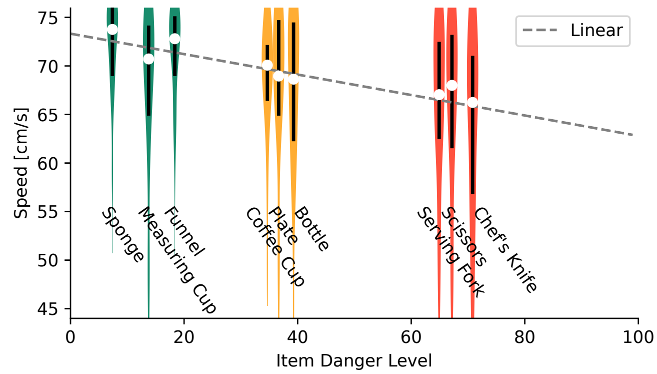


(a) Speed

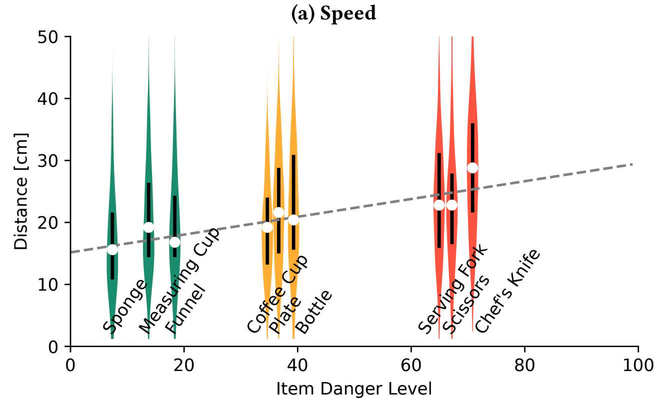


(b) Distance

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



(a) Speed



(b) Distance

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

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 $p > .05$.

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

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

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

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

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

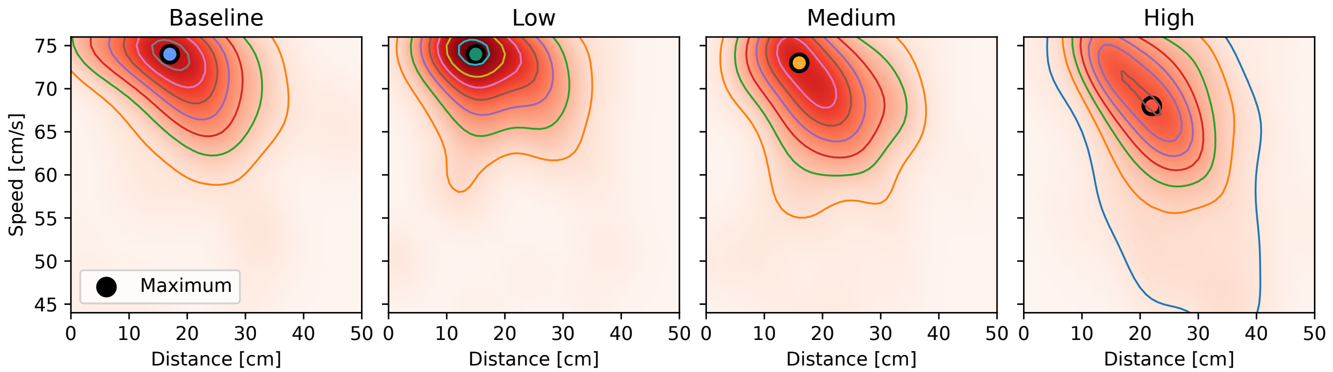


Figure 7: Heatmap of the probability density distribution of Distance and Speed. Darker red areas show more responses and, thus, more agreement. A trend is visible from the maximum to the bottom right, indicating that more dangerous items elicit both larger preferred distances and lower preferred speeds. 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.

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