Push Me: Investigating Perception of Nudge-based Human-Robot Interaction through Force and Torque Sensors

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(a) Tap and nudge interactions. **(b) The study setup.** **(c) *Touchscreen* mode, resembling touchscreen-based interaction of a teach pendant.**

Figure 1: We propose using direct nudges as an intuitive approach to guide a robotic arm to perform a sorting task (left). We compare our proposed approach to controlling the robotic arm with a smartphone (right), in terms of usability, user experience, and workload.

ABSTRACT

Robots are expected to be integrated into human workspaces, which makes the development of effective and intuitive interaction crucial. While vision- and speech-based robot interfaces have been well studied, direct physical interaction has been less explored. However, HCI research has shown that direct manipulation interfaces provide more intuitive and satisfying user experiences, compared to other interaction modes. This work examines how built-in force/torque sensors in robots can facilitate direct manipulation through nudge-based interactions. We conducted a user study ($N = 23$) to compare this haptic approach with traditional touchscreen interfaces, focusing on workload, user experience, and usability. Our results show that haptic interactions are more engaging and intuitive but also more physically demanding compared to touchscreen interaction. These findings have implications for the design of physical human-robot interaction interfaces. Given the benefits of physical interaction highlighted in our study, we recommend that designers incorporate this interaction method for human-robot interaction, especially at close quarters.

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1 INTRODUCTION

Recent advances have enabled the mass production of collaborative robots (cobots), allowing them to enter households [33], health care [24], and industry [5, 14, 22]. Cobots operating near humans have smaller bodies and payloads and are equipped with sensors and safety features to reduce the risk of accidents and injuries [18, 22, 25]. These sensors include force and torque (F/T) sensors, enabling intricate interactions like gesture recognition and biometrics [4, 26, 29].

Traditionally, cobots were programmed through teach pendants or by demonstration, with programming remaining static for the task [22]. Teach pendants have limitations in intuitiveness and ease of use [22, 40]. More intuitive interaction methods include embodied physical interaction [3, 21, 27, 28], known from early Human-Computer Interaction (HCI) research to be more intuitive [34, 35]. These Human-Robot Interaction (HRI) interfaces typically rely on external sensors to capture user input, such as cameras [27], wearables [3, 37], or external F/T sensors [17]. Since modern cobots already have built-in F/T sensors, these sensors can turn the robot arm itself into an input device for haptic interaction. This approach enables designing intuitive direct manipulation interfaces while reducing system complexity by relying on fewer external sensors. However, the usability and User Experience (UX) of physically interacting with a cobot through its built-in F/T sensors have not yet been fully studied.

To address this gap, we created a proof-of-concept prototype where users can control a cobot's behavior by direct nudges and taps. We conducted a controlled laboratory user study with 23 participants to investigate the feasibility, usability, workload, and UX of this interaction method, compared to a more conventional way of control: a touchscreen interface resembling a teach pendant. Our findings show that haptic interactions using internal F/T sensors are usable, have a significantly higher hedonic and overall user experience, and are more intuitive and direct to use, but require significantly more physical effort.

2 RELATED WORK

Direct manipulation is a fundamental paradigm in HCI, introduced by Shneiderman [34], emphasizing visible objects and enabling rapid, reversible, and incremental actions. Building on this, Ishii and Ullmer coined "tangible computing" [15], integrating the physical environment to make digital interactions more intuitive. HRI research has focused on the embodiment of robots and intelligent agents [12, 20, 30], as well as tactile and embodied interaction with these agents [8, 20, 21, 38]. Studies have explored touch- and gesture-based interaction [4, 10, 21, 26–28] and haptic guided assistance [23], typically relying on additional sensors or devices to capture human input and intent, such as Electroencephalography [3], magnetic sensors [16], depth sensors [2], Microsoft Kinect [1, 13], RGB cameras [27], or force/torque (F/T) sensors [17]. Erden and Tomiyama [9] looked into technical implementation details not relying on F/T sensors.

Recent sensor technology and robotics developments have enabled embedding F/T sensors directly in cobots. These sensors can enhance human-robot shared control [7] or infer human intent from gestures [4, 9]. Embedding F/T sensors in robots allows the robots to become input devices. However, cobot interaction and programming still primarily rely on touchscreen-based teach pendants [22, 39]. Weiss et al. [40] and Michaelis et al. [22] examined teach pendants in HRI, particularly in industry, and recommended enabling more intuitive, direct, and physical HRI. Gleeson et al. [10] looked into the user impressions resulting from physical HRI, but did not evaluate workload and UX.

Internal F/T sensors could transform the robot into an input device for haptic interaction. However, there is a notable gap in understanding the usability, user experience, and workload associated with using a robotic arm as an input device have not been thoroughly investigated or compared to traditional interaction paradigms. Our work aims to address this research gap.

3 USER STUDY

In this work, we use the internal F/T sensors of a cobot to turn the robot into an input device for haptic HRI, where nudges and taps could be used to control the cobot. We compare our HRI interface with traditional touchscreen-based interfaces (i.e., teach pendants) in terms of usability, user experience, and perceived workload. We frame our research questions as follows: **RQ1:** To what extent is the built-in force/torque sensor of a collaborative robot usable as a user interface for haptic interactions? **RQ2:** How does sensor-based haptic input compare to traditional touchscreen control in terms of workload, user experience, and usability?

We conducted a user study in a controlled laboratory setting, where participants supervised the cobot and intervened to correct the cobot's actions if it made an error while sorting colored cubes into two different bins. The study setup is seen in figure 1b. We chose the method of input to the robot as the only independent variable. Input could be given in two ways each corresponding to one level of the independent variable: ***Haptic:*** interaction through tapping and directly nudging the robot end effector, and ***Digital:*** pressing buttons on a smartphone's touchscreen, resembling a teach pendant. We followed a within-subject study design, where each participant experienced both conditions. We measured usability using the System Usability Scale (SUS) [6], user experience with the short User Experience Questionnaire (UEQ-S) [19], and perceived workload with the NASA Task Load Index (NASA-TLX) [11]. Perceived safety was measured on a 7-point Likert scale from 1 “least safe", to 7 “most safe", and preferred mode was a choice between "haptic", "digital", or "both equally".

3.1 Participants

We recruited participants through student mailing lists and personal acquaintances. 23 participants volunteered for the study (self-identified: male = 16, female = 6, transgender female = 1), with ages ranging between 21 and 29 years (M = 22.26, SD = 1.88). Four participants reported previous experience with robots, such as playing chess with a robot hand, or doing training with a robotics research group. The rest of the participants did not report previous experience with robots. The study procedure was compliant with the university's ethics guidelines.

3.2 Study Procedure

In the study, participants supervised a cobot sorting red and blue cubes into matching bins. Each trial involved supervising the robot as it processed ten cubes (five of each color), with a predetermined alternating sequence of colors. Participants knew the sequence and could distinguish the colors assigned to each bin. The robot was deliberately programmed to make mistakes 50% of the time, attempting to drop a blue cube in the red bin or vice versa, requiring participants to intervene and correct the robot's actions for five cubes. The order of errors was randomized for each trial, preventing participants from predicting mistakes. Bins were placed on a table between the participants and the robot, marked with colored tape (blue bin on the left, red bin on the right) corresponding to the cube colors (see figure 1b). The robot's speed was deliberately slowed to allow participants sufficient time to see its trajectory and react. Participants could control the robot as follows: **Haptic Control:** A single tap issued the *pause* command. Pushing the robot arm left or right directed it to *drop left* or *drop right*. **Digital Interaction:** The touchscreen interface (see figure 1c) displayed three distinct buttons, each representing a command.

Each participant signed an informed consent form and completed a preliminary questionnaire capturing age and self-identified gender (with the option to not disclose). They were then briefed on the study, the robot, the task, and both interaction methods. Participants practiced the interaction until comfortable with both modes. When ready, the main task began, as described earlier. The study comprised three runs of the main task: one for each interaction method and a third where participants could choose or switch between methods at will. We recorded their choices for the third run. The order of the first two runs was counterbalanced (swapped for each successive participant). Participants were informed about each run's permitted interaction method(s) beforehand. During the touchscreen run, participants could hold the device however they wanted and move freely around the room. The robot arm followed a set sequence to sort cubes: picking them up from the back of the table, moving to a neutral position between bins for participant commands, and then placing the cubes in the designated bin.

Each run lasted about four minutes. After the first two runs, participants filled out a questionnaire about their experience with the interaction method they had just used. After the final run, they completed another questionnaire reflecting on their overall experience, impression of the robot, safety perceptions, preferred interaction mode, and their reasons for this preference. Participants could issue three commands to correct the robot's errors: **Pause**, **Drop left** (drop the cube in the blue bin on the left), and **Drop right** (drop the cube in the red bin on the right). These commands could be combined freely once the robot moved within the participant's reach until the robot dropped the cube. The study took an average of 35 minutes per participant.

3.3 Apparatus

The setup for the study (as seen in fig. 1b) consisted of the UR5e robot arm mounted on a table, with a Robotiq Hand-E gripper[1] attached to the end-effector, to which the haptic taps and nudges were applied. Touchscreen input was issued through a Samsung Galaxy J7 smartphone[2], wirelessly connected to the laptop computer controlling the robot. The handling of F/T sensor data and the coordination of movements were managed by Robot Operating System (ROS), while the gripper was controlled directly via the network, without ROS. The robot operated on URSoftware 5.11.5, provided by the manufacturer. We detected taps and nudges by processing force sensor readings using a simplified variant of a z-score-based peak detection [36].

Incoming force readings were analyzed in two ways: first, for detecting a tap in any direction, and second, for detecting a horizontal push (either left or right). Comparing these results was necessary to accurately identify the intended gesture. For example, the initial impulse of a push might also be detected as a tap. Taps and pushes were detected by comparing the force exerted on the robot's end-effector to predetermined thresholds. If the force surpassed a threshold in either direction, an action was recognized. The algorithm employed for this purpose is a simplified variant of a z-score-based peak detection [36]. This approach considers a finite time-window average of prior readings when checking threshold crossings. This reduces the probability of false positives, e.g. the effect of the robot's movements.

[1]https://robotiq.com/products/hand-e-adaptive-robot-gripper
[2]https://www.samsung.com/us/mobile/phones/all-other-phones/samsung-galaxy-j7-16gb-unlocked-black-sm-j727uzkaxaa/

4 QUANTITATIVE RESULTS

The Shapiro-Wilk test revealed that normality could be assumed for the SUS and the UEQ-S, but not for NASA-TLX. Therefore, significance testing was performed using the Student's paired samples t-test for SUS and UEQ-S results. Data from the NASA-TLX was instead analyzed by pairwise comparison of participant rating of each of the six factors using the Wilcoxon Signed-rank test. We used a significance threshold of $\alpha = 0.05$.

4.1 System Usability

The paired samples t-test showed the difference in average score is statistically significant (t(22) = 3.112, p = .005). The effect size, measured by Cohen's d, was $d = 0.649$, indicating a medium effect (SE = 0.226). The touchscreen received a score of 87.717 SUS score, while the nudge input received 81.630.

4.2 User Experience

The paired sample t-test showed that the means are significantly different across the pragmatic, hedonic, and overall qualities. The results the following, with negative t values indicating higher scores for haptic interaction, and effect size given using Cohen's d:

- **Pragmatic Quality**: $t(22) = 4.217, p < .001$. $d = 0.879$, indicating a large effect (SE = 0.280).
- **Hedonic Quality**: $t(22) = -6.875, p < .001$. $d = -1.434$, indicating a very large effect (SE = 0.383).
- **Overall Quality**: $t(22) = -4.407, p < .001$. $d = -0.919$, indicating a large effect (SE = 0.305).

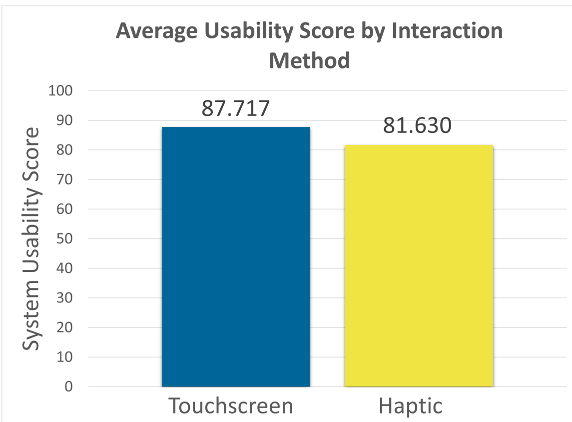
4.3 Workload:

Wilcoxon signed-rank test for pairwise comparison of NASA-TLX factors between touchscreen and haptic interaction showed the following results, with effect sizes for significant differences given using the rank-biserial correlation r (negative z values indicate higher scores for haptic interaction):

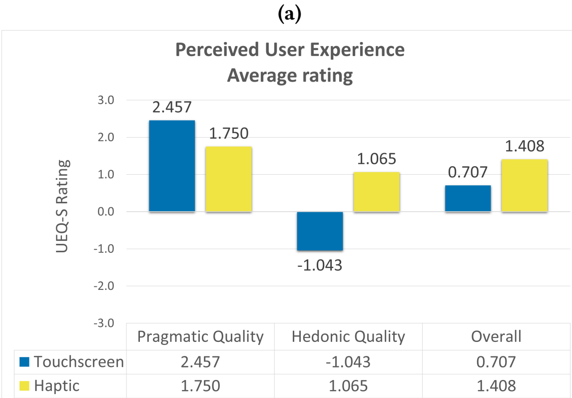
- **Average Workload**: $W = 27.500, z = -3.214, p = .001$, $r = -0.783$ (SE = 0.239), indicating a large negative effect.
- **Mental Demand**: $W = 32.500, z = -0.909, p = .364$
- **Physical Demand**: $W = 0.000, z = -3.823, p < .001$, $r = -1.000$ (SE = 0.256), indicating a large negative effect.
- **Temporal Demand**: $W = 14.000, z = -1.689, p = .090$
- **Performance**: $W = 2.500, z = -1.348, p = .203$
- **Effort**: $W = 15.000, z = -2.556, p = .010$, $r = -0.750$ (SE = 0.285), indicating a large negative effect.
- **Frustration**: $W = 42.000, z = -0.245, p = .832$

Table 1: Descriptive statistics for raw NASA-TLX ratings by the participants. Minimum and maximum values denote the lowest and highest ratings given by the participants for each category.

	Touchscreen					Haptic				
	Mean	Std. Deviation	IQR	Minimum	Maximum	Mean	Std. Deviation	IQR	Minimum	Maximum
Mental	2.609	2.251	1.50	1	10	2.870	2.074	2.00	1	8
Physical	1.174	0.388	0.00	1	2	2.826	1.875	1.50	1	8
Temporal	1.739	1.356	1.00	1	7	2.174	1.370	2.00	1	6
Performance	1.130	0.344	0.00	1	2	1.304	0.635	0.00	1	3
Effort	1.739	0.964	1.00	1	4	2.870	2.160	2.00	1	9
Frustration	2.478	2.609	1.00	1	12	2.565	2.905	2.00	1	14
Average	1.812	1.086	0.67	1	5.333	2.435	1.417	1.25	1	6.333



(a)



(b)

Figure 2: a) Average SUS score for each method of interaction. b) Average UEQ-S rating for each quality and overall value. A higher value signifies a better evaluation. Ratings > 0.8 are considered positive, ratings between 0.8 and -0.8 are considered neutral, and ratings < -0.8 are considered negative [32].

The *physical demand* and *effort*, as well as average workload are found to be significantly different. Visualizations can be seen in fig. 3 and table summaries can be found in table 1.

4.4 Preferred Mode and Perceived Safety

Participants' preferred mode of interaction was captured using a choice between haptic, digital, and "both about the same". Out of 23 participants, nine preferred the haptic mode, nine preferred the digital mode, and five chose "both about the same". We also tallied the participants' self-reported perception of safety during each of the first two trial runs on a 7-point Likert scale, with 1 being "least safe", and 7 being "most safe". One participant rated the safety of the digital interaction at 6, while the 22 other participants rated it as 7 ("most safe"), resulting in an average safety rating of 6.96. For haptic interaction, three participants rated the safety at 5, eight participants rated it at 6, and the remaining twelve rated it at 7. This resulted in a mean rating of 6.39.

5 QUALITATIVE RESULTS

At the end of the study, participants completed a concluding questionnaire with open-ended questions about their initial impression of the robot, their overall experience interacting with it, and their preferred method of interaction. Responses were segmented into distinct statements and analyzed using thematic analysis by three researchers, two of whom are authors. The analysis yielded two clusters of themes: one focused on specific modes of interaction and the other on the overall experience with the robot. The cluster related to interaction modes consists of eight themes: **Intuitiveness** (ease of understanding the interaction method), **Novelty** (feeling new or unique), **Physical ease** (lack of physical strain), **Interactivity** (dynamic engagement), **Proximity** (physical distance), **Consistency** (reliability over time), **Responsiveness** (quick reactions), and **Safety** (feeling free from threats or injury).

For the haptic nudges, participants described it as a "natural way of interaction" and were "fascinated by the way the robot reacts to nudges." Participants remarked that nudging was "not tedious," while interactivity was praised for giving "instant feedback." Short distance interactions were preferred, with one comment stating, "hand interactions seem better for short distance." Consistency and responsiveness were positively noted: "The robot understood [the instructions] rather clearly" and "It reacted quickly." Safety was perceived positively because the robot was "slow and predictable."

For the touchscreen mode, participants found it "very [convenient] to use," likening it to their daily smartphone interactions.

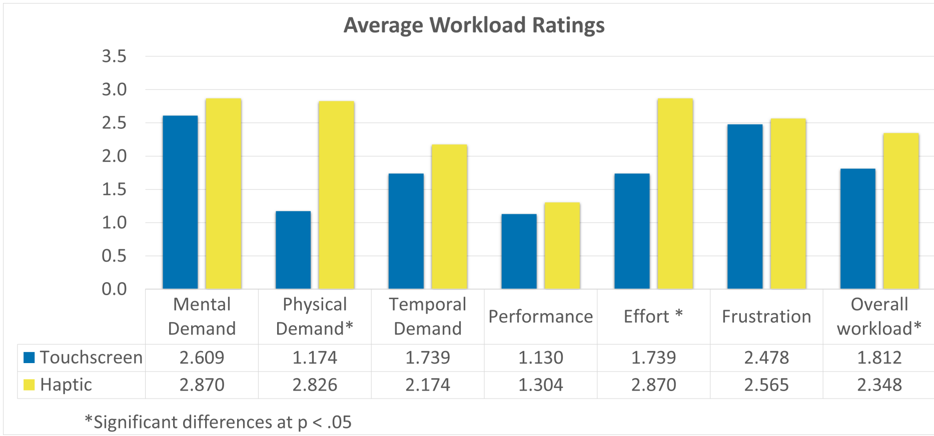


Figure 3: Results of the mean NASA-TLX values for each factor. A lower value expresses lower task demand.

Physical ease was highlighted as needing "less strength to direct the cobot," and interactivity was described as "more [convenient] to communicate." Remote capability was appreciated: "I can perform the action from everywhere and do not have to stand next to the robot to change the direction." Consistency and responsiveness were positively noted, with fewer control errors and quicker interactions.

The overall experience themes reported by participants were categorized into three main themes: the robot being slow, the task being boring, and safety not being a concern. Participants found the robot "too slow to be used in a professional environment," the task "got a bit boring after the first few times," but felt "never insecure or anything similar" and could "easily trust the robot." A summarized list of participant comments can be found in the appendix.

6 DISCUSSION

Haptic Interactions for Cobots Are Usable and Enjoyable. Although the SUS usability scores were significantly different, both modes scored in the 90th percentile, considered *excellent* by Sauro [31]. This indicates the feasibility of haptic interactions, answering **RQ1**, and supports testing more complex gestures such as a handshake [29]. Simple gestures, e.g. tapping someone's shoulder to get their attention, can be mimicked using internal F/T sensors, enabling social robots to respond to light touch. We propose that building on this capability, a robot that can sense light touch can be *gentle*, a quality that may increase acceptance and trust in settings such as healthcare. Designers of service robots in such settings can use this method's usability to inform their designs.

Direct Physical Interactions Are More Pleasant but Situationally Practical. UEQ-S results show that both modes received positive evaluations for pragmatic quality, with the touchscreen mode scoring significantly higher. Participants commented on the straightforwardness of touchscreen interactions; when the button is pressed, the robot reacts. The ubiquity of touchscreen devices (e.g., smartphones, tablets) normalizes this interaction. Some participants had difficulties with the haptic mode, as the robot occasionally failed to register inputs, especially during the pre-trial practice run. Despite this, the positive pragmatic evaluation of the haptic mode is promising. The hedonic quality ratings show a stronger difference, with the haptic mode receiving a higher rating. Participants described touchscreen control as "boring" and haptic control as "fun", suggesting haptic interaction felt novel, while on-screen buttons were not exciting. The positive hedonic evaluation of haptic interaction is likely due to direct manipulation being more intuitive than the touchscreen interface, combined with the initial novelty of haptic interaction, resulting in a better user experience. This aligns with previous findings [12] and answers **RQ2**. However, the situational usefulness of direct haptic input should be considered. Our study's robot was slowed down, and the task was easy. In industrial settings demanding speed and efficiency, physical human-robot interaction would be impractical and unsafe. However, in contexts like domestic support, agriculture, or healthcare, where a helper robot moves slowly and operates near humans, physical interaction could guide the robot or serve as an additional modality. Participant comments suggest tactile interactions are more intuitive and feel more "natural".

Physical Proximity and Task Load. NASA-TLX results show statistically significant differences in physical demand, effort, and overall workload. Touchscreen interaction scores lower in these categories, indicating better performance. The higher physical demand and effort for the haptic method could be due to the need to physically reach out to give commands. Similar levels of perceived performance and frustration suggest participants found the haptic method satisfactory, comparable to the touchscreen, despite needing to adjust to sensor sensitivity. Participants' comments indicated that the touchscreen mode was easier, requiring only finger movements rather than using the entire arm and less strength. This suggests the touchscreen mode's advantage is its physical ease and remote usage capability, while haptic interaction was enjoyable with appreciated tactile feedback. However, the physical movement and effort required by haptic interaction are intrinsic to this input method. This has implications for haptic interface design; significant physical effort could outweigh the benefits of intuitiveness and user experience (UX). Designers should ensure haptic interfaces are not overly tedious by avoiding reliance on elaborate movements. Usability and UX are also influenced by the compliance of robot joints and the effort required for haptic inputs.

Haptic Interactions Are Safe, With Precautions. The perceived safety results suggest that close interaction can reassure robotics novices when precautions like slowing down the robot and allowing an adjustment period are taken, as seen in our pre-task trials. The even distribution in participant preference between the two interaction methods indicates that each had its benefits and downsides. Participant comments generally align with the quantitative results. Although the haptic trial was rated slightly lower in perceived safety, this did not noticeably impact participants. Only one comment addressed safety, positively noting the robot's safety during the haptic trial. However, the robot's speed was intentionally limited, and many participants found it slow, as their comments reflect. Thus, participants' safety perceptions might change if the robot's speed were increased. Safety ratings in high-speed industrial contexts are expected to differ significantly from slower, less time-critical contexts like social and domestic settings. This suggests that users do not find physical interaction with a robot inherently dangerous. Designers should consider this for social use-cases; if the robot's movements and speed are not inherently threatening, users are likely willing to interact physically with it.

Limitations and Future Work. The participants were mostly computer science students of similar ages and technical backgrounds. Future work should include more diverse participants from various demographics. To gauge participant reactions to proximity to a moving robot, we slowed down the movements of the prototype and chose a simple task with predictable straight-line trajectories. The results encourage further studies at higher speeds, with more complex tasks and gestures, such as rotational inputs, to further explore usability and user experience. We acknowledge the limited timespan of our study and the potential impact of novelty effects in evaluating haptic feedback. Future studies should involve participants more experienced with robotics to eliminate confounding novelty effects. Future developments can focus on implementing a wider range of inputs and integrating haptic interaction with other modalities, such as speech. Subsequent work should explore the effect of higher robot speed on perceived safety and overall impressions in more use cases of physical interaction, allowing usability testing in tasks like object handover.

7 CONCLUSION

We examined the usability of a proof-of-concept HRI interface that uses the internal force/torque sensor of a cobot to enable direct physical interaction. The cobot itself becomes an input device for direct physical interaction by nudging and tapping. We compared the usability, user experience, and workload to those of a traditional touchscreen interface. Haptic interaction was perceived as more enjoyable and engaging, receiving a higher hedonic quality score. Participants highlighted a difference in physical effort between the touchscreen and haptic control modes, with nudges being perceived as more physically demanding. Overall evaluation suggested that haptic interactions are as viable as a touchscreen-based method to control the robot. The results show that both modes of interaction were evaluated positively in terms of pragmatic quality, with haptic interaction receiving a slightly lower rating. Participants did not perceive any inherent significant safety issues while physically interacting with the robot at an intentionally slow speed. Participants perceived haptic interaction to be an engaging alternative to traditional interfaces for controlling the robot. The results show that this interaction method is usable and that this direction offers a promising foundation for further research. We expect future work to further investigates the UX and perceived workload of this interaction method with more complicated gestures in more specific contexts.

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A SUMMARIES OF STATISTICAL TEST RESULTS

Table 2: Student's paired samples t-test comparing pragmatic, hedonic, and overall UEQ-S qualities. Negative values for t signify haptic interaction scoring higher.

Touchscreen vs. Haptic	t	df	p
Pragmatic Quality	4.217	22	$< .001$
Hedonic Quality	−6.875	22	$< .001$
Overall	−4.407	22	$< .001$

Table 3: Wilcoxon signed-rank test for pairwise comparison of NASA-TLX factors. Negative values for z signify haptic interaction scoring higher.

Touchscreen vs. Haptic	W	z	p
Average workload	27.500	−3.214	0.001
Mental Demand	32.500	−0.909	0.364
Physical Demand	0.000	−3.823	$< .001$
Temporal Demand	14.000	−1.689	0.090
Performance	2.500	−1.348	0.203
Effort	15.000	−2.556	0.010
Frustration	42.000	−0.245	0.832

B SUMMARIES OF RESPONSES TO OPEN-ENDED QUESTIONS

Table 4: Qualitative comments about the overall experience.

Theme	n	%	Sample comments
Slow	14	52%	"The robot moves in areas where no interaction is plan very slow." "It is to slow to be used in a professional environment." "But it was slower than I expected."
Boring Task	6	22%	"However it got a bit boring after the first few times." "Personally, I would have a problem of focusing on the task for a longer time."
Safety	7	26%	"It seems to be very safe." "Never felt insecure or anything similar." "[...] I can easily trust the robot."

Table 5: Qualitative comments about the haptic nudges interaction method.

Theme	Sentiment	n	%	Sample comments
Intuitiveness	Positive	10	17%	"Natural way of interaction." "Tactile sense is enough to tell where the robot is without looking at it."
Novelty	Positive	6	10%	"I'm fascinated by the way the robot reacts to nudges." "It was more exciting to interact directly with the robot."
Physical ease	Positive	1	2%	"Not tedious."
	Negative	3	5%	"I would like to spend less physical effort." "Need to move more and use physical action."
Interactivity	Positive	23	40%	"It gives instant feedback." "Something to do with both hands and mind."
	Negative	2	3%	"Felt odd sometimes."
Proximity	Positive	4	7%	"Hand interactions seem better for short distance." "Preferred when the robot is close."
Consistency	Positive	4	7%	"The robot understood [the instructions] rather clearly."
	Negative	3	5%	"The sensors could be more sensitive."
Responsiveness	Positive	1	2%	"It reacted quickly."
Safety	Positive	1	2%	"Safe because slow and predictable."

Table 6: Qualitative comments about the touchscreen mode.

Theme	Sentiment	n	%	Sample comments
Intuitiveness	Positive	3	8%	"It was very [convenient] to use, because interacting with a smartphone on daily basis helps."
Novelty	Positive	1	3%	"During the digital use you [feel] like a scientist."
	Negative	5	14%	"I am pretty sure that using the phone would get boring rather fast and thus, make one less attentive." "I think that using the [touchscreen] interaction takes away the collaborative aspect a bit."
Physical ease	Positive	9	24%	"It needed less strength to direct the cobot." "It is easier to push a button than use muscle strength to redirect [the robot]."
	Negative	2	5%	"With the [touchscreen] mode, I always had to move my head up and down, first to click the correct button, then to check if the robot had actually [received] the command and acted appropriately."
Interactivity	Positive	2	5%	"[with the phone] it is more [convenient] to communicate."
	Negative	1	3%	"It is possible to confuse the right and left button on a screen by a tall user."
Proximity	Positive	8	22%	"You can do it [remotely]." "I can perform the action from everywhere and do not have to stand next to the robot to change the direction."
Consistency	Positive	2	5%	"Control errors like stopping accidentally did not happen with the phone."
	Negative	1	3%	"Sometimes the buttons on the [touchscreen] version would only register after a second tap though, which was a bit annoying."
Responsiveness	Positive	3	8%	"The interaction was quicker."