Calibrated Human-Robot Teaching: What People Do When Teaching Norms to Robots

Vivienne Bihe Chi and Bertram F. Malle

Abstract—Robots deployed in social communities must act according to the communities’ social and moral norms. To acquire the large number of nuanced norms, robots can rely on human teaching. While humans tend to naturally use more than one teaching method when training a novice, current human-in-the-loop teaching frameworks have typically relied on single teaching methods (e.g., instruction or reward). To gain insight into how humans would teach robots to master social and moral norms, we present a novel paradigm in which participants interactively teach a simulated robot to behave appropriately in a healthcare setting, choosing to either instruct the robot or evaluate its proposed actions. We demonstrate that 89.5% of human teachers naturally use both teaching methods. Importantly, they adapt their teaching method as they observe the robot’s task performance, responding dynamically to the task’s difficulty, the robot’s most recent action, and the accumulated evidence of the robot’s learning progress.

I. INTRODUCTION

Embodied artificial agents are becoming increasingly present in people’s daily lives as assistants and collaborators. When acting in these roles within a given social context, robots are expected to follow the relevant social and moral norms—the directives shared by a community on how one should and should not behave in this context [1]–[3]. Because social contexts are complex and ever-evolving, purely unsupervised learning of norms from large training data will be unlikely to succeed. Instead, humans would make ideal teachers for robot learners [4], [5].

Interactive human teaching is particularly important for robots deployed in social settings, where a large number of often subtle norms govern social behavior [6], [7]. How could robot designers harness the power of human teaching and thus enable robot to learn and comply with social and moral norms? The obvious prerequisite is that robots must be able to benefit from people’s natural way of teaching—that is, their algorithms must be receptive to such teaching. However, to devise such receptiveness, we must answer a critical question: whether humans are able and willing to teach a robot norms and, if so, how they do it. Approaching an answer to this question is the goal of the current paper.

Much of the previous work on human-robot teaching was guided by the robot learner’s limitations. For example, because most robots are not equipped to perform one-shot learning, a robot will repeatedly ask for human feedback on the same task and place the burden on the human teacher to consistently produce high-quality feedback [8]–[10]. In addition, because learning algorithms have been optimized for one type of learning (e.g., from scalar feedback or from demonstration), human teaching has been usually limited to a single teaching method [11], which could reduce the quality of teaching. In initial efforts, researchers have tried to reduce these limitations by designing learning algorithms that adjust to inattentive or inaccurate human teachers [12], that learn reward functions from more than one type of information [13], [14], and that respond to teaching data of various formats [15]. However, very little work has shed light on how people would naturally teach robots, and even less work has examined who people could possibly teach robots to learn norms. In this study, we close this gap by studying humans’ natural teaching behavior when training robots to acquire norms, and we hope this study will inform the design of improved robot learning algorithms.

II. RELATED WORK

A. When Humans Teach Humans

In the educational and developmental literatures, two broad teaching strategies have been contrasted: (1) the teacher instructs the learner or (2) the teacher lets the learner explore and discover [16] and provides guidance with varying amounts of feedback [17].

When a learner does not yet know how to approach a problem or how to acquire relevant information, a teacher typically chooses to instruct the learner so they can access the critical information [18]. Instruction could be in the form of verbal description, non-verbal action demonstration, or a mix of both. Demonstrations are often strategically regulated by the teacher to facilitate learning. For example, teachers often use intentional speech acts or exaggerate some parts to help guide the allocation of attention [19]. Demonstrations generated from the teacher’s point of view are manifestations of the teacher’s understanding, and they still require further steps on the learner’s part to achieve internalization [20]. However, children do seek less information after seeing adult demonstrations, because they assume adults are omniscient and what had been demonstrated is all there is to learn. As shown in [21]–[23], instructed learning is not always optimal and can sometimes hurt children’s creativity and hamper internalization.

Alternatively, when a learner has access to the relevant information but is not paying enough attention to it, or over- or under-uses certain information in their attempts, teachers
often choose to supplement a learner’s exploration with evaluative feedback [18]. This teaching method demands more social inference skills from the learner, as the feedback itself does not directly give away the desired behavior. When it comes to teaching norms, in particular, humans use evaluative feedback such as praise or blame to shape the learner’s behavior. Children then use this feedback to try to infer the norms they are expected to follow [24], [25]. Interestingly, while proper reward feedback is essential for effective socialization [26], norm-compliant behaviors are rarely rewarded because the social environment is teeming with such norm compliance. Parents more often express disapproval for norm violations or threaten sanctions to dissuade norm-deviant conduct.

Choosing one or the other major teaching method—instruction vs. evaluative feedback—involves a trade-off between direct intervention and allowing learning from mistakes. Some teachers adopt a personal teaching style that favors one or the other side of this trade-off [27]. But many teachers employ a mixed strategy, in an attempt to strike a balance between informative instruction and freedom for exploration. In guided play, for example, child exploration is melded with teacher-guided instruction [17], [28], [29]. To make a mixed teaching strategy work, a teacher needs to maintain updated inferences of the learner’s intention and capacities and choose the appropriate teaching method accordingly [30].

### B. When Humans Teach Machines

We know a fair amount about human-human teaching, but, as [31] recently asked, to what extent do humans extend their ordinary teaching strategies to robots? The answer to this question informs whether we can use principles of human-human teaching as a helpful framework for human-robot teaching. Some research in HRI does suggest that human teachers transfer some of their habits of teaching other humans to their new task of teaching robots.

When engaging with a robot, human teachers can choose between an analogous pair of teaching methods. They can give direct action instructions (by demonstration, prior programming, or verbal commands) [32]–[34] or they can let the robot explore possible actions on its own and give evaluative feedback that encourages or discourages those actions [35]. An active learning agent should be able to learn from all of these different teaching methods, as humans may use them flexibly towards robots just like they do toward other humans [36], [37].

To start with, human users can train the agent by giving verbal instructions or nonverbal demonstrations. Demonstrations are often the default and natural strategy for human teachers, especially when they have yet to develop a mental model of the learner. One way an agent can learn from such demonstrations is inverse reinforcement learning (IRL). This class of algorithms enables the agent to infer from a series of observations a reward model that induces an optimal policy (action strategy) consistent with the observed (“correct”) human behaviors [8], [38]–[40]. Alternatively, humans can assess the agent’s past actions and provide evaluative feedback to train the agent [9], [10], [41].

Each of the two teaching methods has advantages and disadvantages. Instruction or demonstration are information-rich, therefore may dramatically accelerate a robot’s learning. However, it may be challenging for ordinary people to generate multiple demonstrations that a robot would need. Moreover, people’s demonstrations might sometimes fail to display what they themselves actually want. For instance, in Basu and colleagues’ [42] study, people demonstrated a driving style on the simulator that they thought they would prefer as a passenger, but when the autonomous vehicle chose that style, people found it too aggressive.

Teaching by evaluation allows the agent to explore the option space with more freedom and affords the possibility to surpass human performance. However, it is easy to see that freedom can lead to errors and, especially in the social domain, such errors can be costly and prevent users from continuing to interact with the robot.

Unfortunately, most computational teaching frameworks do not give human teachers any choice of teaching method but assign them a single fixed teaching strategy [43], [44]. As we know from real-life pedagogical scenarios, teachers strategically mix and vary their mode of instruction as learning progresses. Though providing demonstration often requires greater effort from the teacher, research has found that teaching by demonstration and evaluation are equally natural for human trainers [45], [46]. Some studies suggest that human teachers tend to give demonstrations first and follow up with evaluative feedback to fine-tune the learned behavior [47], [48]. But this may not always be the preferred pattern.

Recent algorithmic work has started to see the benefit of mixed-method teaching [49], [50]. Researchers have devised algorithms that integrate learning from demonstrations with preference-based feedback in interactive teaching settings [13], [37], [51]–[53]. And in our own work [54], [55], we have demonstrated that an agent can learn context-specific norms by inferring reward functions from various types of teacher feedback and generates policies maximally likely to satisfy the teacher’s intended norms.

Ultimately, to optimize robot learning from human teachers we need to better understand how ordinary people naturally teach robots. And that is particularly true in the case of teaching norms, which might be best achieved by ordinary people in ordinary social settings, performing a kind of robot socialization. In the present study we aimed to simulate such socialization, but we retained a high degree of experimental control in order to assess not only whether people use mixed methods (instruction and evaluation) when teaching a robot but how sensitive they are to number of variables in the robot’s unfolding performance.

We targeted experimental realism in the interface and the teaching process (see below), but we abstracted away from several features of a real-world teaching session. We restricted interactions with the robot to text-based exchanges in order to minimize undue influence from robot voice and
appearance factors. Also, we omitted a visual information channel in order to reduce distractions, and we presupposed that the robot had excellent perception and motor skills so people could focus on norm-appropriate action as the essential target of teaching. Finally, we introduced the robot as already having a certain familiarity with norms, and the primary teaching purpose was to tune, update, and refine the robot’s norm-guided behavior—which may be the most promising way of fostering robots’ norm competency [3].

III. STUDY OVERVIEW

In this study we investigated people’s strategic choice of teaching method within an interactive teaching setting. Participants assumed the role of assisting a robot in performing several healthcare tasks in a norm-appropriate way. Throughout the study, participants were required to teach the robot various tasks by either offering action instructions to the robot or providing evaluations of the robot’s action proposal.

We experimentally manipulated the displayed robot learning trajectory over the course of the training session: Participants were randomly assigned to teach either a fast-learning robot or a slow-learning robot. We hypothesized that probability of instruction vs. evaluation will be sensitive to this overall learning rate, as well as to the robot’s most recent behavior, and the current task difficulty. Specifically, we tested whether (1) people instruct the fast-learning robot less than the slow-learning robot; (2) people instruct the robot less when it recently displayed appropriate action proposals; (3) people instruct the robot less when it displayed an accumulated history of appropriate action proposals; and (4) people instruct the robot less for tasks perceived to be less difficult.

IV. METHODS

A. Platform

In [36] we designed a smartphone-based experimental interface for human-robot communication (cf. [56], [57]) that allows participants to engage in an interactive training session with a robot agent (Fig. 1). The top part of the screen mimics a messaging application (“chat app”) where robot and human teacher communicate via short messages. In the area below the chat app, participants (a) select a teaching strategy for the current task (e.g., to instruct or to evaluate), (b) provide specific teaching feedback (e.g., selecting an appropriate action instruction or a specific evaluative rating), and (c) respond to trust measurement questions. All participants were required to complete the experiment on smart phones.

B. Participants

We recruited 220 participants on Prolific (http://prolific.co). To account for possible attrition we aimed for a slightly larger sample size than the intended \( n = 100 \) for each between-subjects condition (for statistical power of \( \alpha < .05 \) to detect an effect size of \( \delta \geq .40 \)). Recruitment and procedures were approved by the Brown University IRB.

C. Procedure and Design

We first gave participants very brief background information on healthcare robotics. Then we invited them to act in the role of a busy nurse delegating some hospital tasks to a healthcare robot. Participants were told that the robot is generally competent at the tasks, but they were responsible for training it to act norm-appropriately when the robot consults with them.

The robot training session consisted of five training days, each featuring an easy task (e.g., politely knocking before entering a room), a moderate task (e.g., enforcing a non-smoking rule), and a difficult task (e.g., handling patient complaints). These task scenarios were selected to implicate one or more social-moral norms while representing the tasks a robot nurse assistant would likely to perform. For each task scenario, we prepared an inappropriate, acceptable, or appropriate action, in light of context-relevant norms. For example, for a scenario of seeing a patient’s family member smoke in the hospital room and the goal of enforcing the non-smoking rule, the appropriate action was to announce a gentle reminder, the acceptable action was to make some noise, and the inappropriate action was to not intervene.

For each task, the robot initiated the learner-teacher interaction by describing its current environment (e.g., at the elevator), its goal (e.g., I need to go downstairs), and specific context (e.g., other people are waiting ahead). Following the robot’s description of the environment, goal, and context, participants expressed their feelings of trust in the appropriateness of the robot’s next action.

Next came the critical decision of teaching method—whether to instruct the robot or evaluate its proposal. To choose the Instruct option, participants would click “Here’s what you need to do” and selected one of three possible actions (Fig. 1-middle). The robot would reply with “Noted!” along with its own original plan of action, phrased as, “I was planning to...”. To choose the Evaluate option, participants would click “Let me hear your proposal”, which would trigger a display of the robot’s planned action for the current task, the participant would evaluate that proposed action on a five-point rating scale marked by the labels “That’s forbidden,” “... discouraged”, “... allowed”, “... appropriate,” and “... required.” (Fig. 1-right). The robot would respond with “Got it. Thanks!” This procedure ensured that participants always learned about the quality of the action that the robot was prepared to take, irrespective of the participant’s teaching decision. A “Continue” button appeared at the bottom of the screen that initiated the next trial.

Additional trust measurements were taken at the end of each of the five training days and at the beginning and the end of the training session. These results are reported in detail elsewhere [58], but we will briefly relate trust and teaching method in the Discussion section.

Evidence for learning progress was controlled by means of a fixed scheme of action proposals that, over the course of the five training days, increased in quality. These action proposals were designed to be clearly inappropriate, ac-
ceptable, or clearly appropriate. To validate this designation we asked a sample of participants ($N = 70$) to rate the quality of the robot’s proposed actions on appropriateness, using a 1-5 scale. The resulting mean ratings became each action proposal’s assigned level of appropriateness, which was treated as a continuous predictor in statistical analyses.

We implemented a between-subjects factor of slow vs. fast robot learning rate by designing two trajectories of task performance with different slopes of improvement. Both robots improved over the course of the training days, but the fast-learning robot improved more quickly than the slow-learning robot. While both robots started at the same level, only fast-learning robots reached near-perfect level of performance toward the end of the training session. Specifically, the distribution of behaviors originally designated as inappropriate–acceptable–appropriate behaviors was 2–5–8 across the 15 tasks for the fast-learning robot and 4–8–3 for the slow-learning robot. (For details of this improvement scheme, see the Supplementary Material [59]).

V. RESULTS

Participants were free to use either one of the two teaching strategies (instruct vs. evaluate) in each of 15 trials. Of the 220 participants, 89.5% adopted a mixed teaching strategy, 3.6% chose to always give action instructions, and 6.8% chose to always evaluate the robot’s proposals. Given that most people used a mixed teaching strategy, we aimed to predict their strategy choice at each step of the training process.

To begin, a person’s teaching method choice for the very first task should only be influenced by their own general teaching style (tendency to choose one teaching method over the other), as the robot learning rate manipulation was not yet shown. An initial generalized linear model showed that a teacher’s broader tendency (percentage of instruction choices over the last four training days) predicted their teaching method choices on the first training day ($z = 3.48, p < .001$), while the robot learning rate manipulation had no significant impact ($p = .11$).

We then built a model to predict people’s teaching method choices throughout the five training days and found a decrease in the tendency to offer instruction over time. After the first training day (baseline, $M_{day1} = 0.46$), probability of instruction slightly increased in the second block ($M_{day2} = 0.52$), then declined throughout the remainder of the training days ($M_{day3} = 0.47, M_{day4} = 0.44, M_{day5} = 0.36$), $z = -6.864, p < .001$. (Fig. 2). Moreover, the rate of decline was steeper for fast-learning robots $z = -4.042, p < .001$. This pattern of results suggests that, after a brief surprise of less expertise than they may have expected (day 1 to 2), people noticed the robot’s continued improvement and became confident that it deserved more autonomy.

Recall that when people chose to evaluate, they gave the robot’s proposed action a 1-5 rating. The overall mean of evaluations was toward the positive side ($M = 4.14$), reflecting the experimental design in which the robot’s action pro-
Fig. 2. Human teachers briefly increased use of instruction in the beginning, then increasingly favored evaluation of the robot’s proposals as robot progressed through the training session, and did so more quickly for the fast-learning robot.

posals tended toward appropriateness. Importantly, people’s evaluation scores for the robot’s proposals were responsive to the level of appropriateness of the proposals. Evaluation ratings for action proposals were linearly increasing with more appropriate action proposals, $t = 22.28, p < 0.001$.

Next, we used a generalized mixed effects model with subject as a random effect to examine which factors predict people’s teaching method choices (instruct or evaluate) in each teaching trial. We entered the level of appropriateness of the robot’s action proposal quality in the previous trial as one predictor. We also entered a measure of the accumulating evidence of learning, which computed, at each trial starting with the second, the sum quality score (from pretest) of all previous action proposals the robot made. This sum score weights both the quality and number(stage in the training session) of proposals the participant had witnessed. We found that this accumulated learning score linearly predicted a lower probability of instruction, $z = -5.03, p < .001$.

Further, even though the robot’s action proposal quality in the previous trial did not by itself contribute to the probability of instruction, it interacted with the accumulated learning evidence, $z = -3.18, p = .001$. As the robot’s improvement became more palpable through the accumulated evidence of learning, a recently observed highly appropriate proposal further decreased people’s probability to instruct the robot in the following trial; but an inappropriate action proposal (which was surprising, given the accumulated learning evidence) increased people’s probability to instruct (Fig. 3). Instruction thus served to return the robot onto the right path when there was an unexpected inappropriate action proposal.

Finally, we introduced task difficulty of the current trial as an additional predictor and found that people were more likely to choose instruction for more difficult tasks, $z = 4.07, p < .001$.

VI. DISCUSSION

This experiment used a recently developed human-robot teaching paradigm to examine which methods human teachers choose when interactively training a social robot. The primary dependent variable was people’s choice to instruct the robot (implying less confidence in the robot’s ability to act appropriately) or evaluate the robot’s proposal (implying more confidence). We found that people were attentive and engaged in the teaching task and highly systematic in their teaching choices, showing sensitivity to several aspects of robot performance and to task difficulty. We discuss the results and their implications and offer a tentative interpretation involving the role of growing trust in teaching.

A. Calibrated Teaching

Instead of manipulating people’s initial expectation for the robot’s capabilities (as in [36]), the present study manipulated the robot’s learning rate over the course of the training. After an initial hint of skepticism (increase of instruction from day 1 to day 2), people increasingly favored evaluation of the robot’s proposals, but more quickly so for the fast-learning robot. In addition to this overall growth of confidence in the robot’s competence, teachers’ choices were strongly influenced by the local (trial-by-trial) and accumulated evidence they gathered of the robot’s learning progress. People’s teaching choices carefully tracked both the appropriateness of the robot’s most recent action proposal and the gradually stabilizing evidence of the robot’s learning progress. In addition, they took into account the difficulty of every task at hand, shifting to preventive instruction for difficult tasks. We can call this teaching behavior “calibrated” because it is systematically responsive to objective events in the environment, and in the expected direction (e.g., more instruction when performance is low).

These findings suggest that people are motivated and highly suitable to teach norms to robots. Even though they may have a personal preference overall for one teaching strategy over the other, they use several sources of evidence gathered over time to calibrate both their teaching strategy choices and their fine-grained evaluation scores. Robot learning algorithms must in turn harness such calibrated teaching
by being responsive to both instruction and evaluation [55] and by offering continued evidence of performance that is useful for teachers. Over time, even less monitoring and management may be possible, such that human teachers delegate numerous tasks to the robot and assume it will consult with the human when its norm-appropriate action planning is at an impasse.

B. Teaching and Trust

The present experiment included a battery of trust assessments that we set aside for the current analyses of teaching choices. Elsewhere, however, we reported on these dynamic updates of trust in response to the robot’s learning progress [58]. These parallel dynamics of trust and teaching strategy choices, both in keen response to robot performance, suggest the interpretation that people make their teaching choices because they increase trust in the robot’s norm competence. Indeed, when analyzing the parallel streams of measurement we see that people’s growing trust feelings went along with choosing to instruct less, $z = -6.078, p < .001$, and that was especially true when they had accumulated strong evidence of robot learning, $z = -3.31, p < .001$.

This result alone does not secure a causal interpretation. Growth of trust may not itself cause teaching choices, but one’s self-perception of teaching choices may lead to trust growth (“I am letting the robot propose its next actions; I must trust the robot!”). We will test this hypothesis by assigning people to use one or the other teaching strategy and by assessing whether trust dynamics continue to be responsive solely to robot performance or (also) to the self-perception of teaching choices.

VII. CONCLUSION

We have used a novel experimental paradigm to examine whether laypersons would be willing and able to teach norms to robots. We conclude that they are and that they show systematic calibration of their teaching strategies to robot performance and task characteristics. Moreover, there is evidence that people’s trust in the robot is at least a correlate, if not a cause of these teaching choices. If robots’ learning algorithms can be designed to make use of people’s well-calibrated teaching of norms, then social robots may indeed become members of human, or rather human-robot, communities.

REFERENCES

Supplemental Material for *Calibrated Human-Robot Teaching: What People Do When Teaching Norms to Robots*

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**Reference of source article**


**Pre-programmed robot performance**

In the original design of the experiment we had designated the 15 task behaviors as appropriate, acceptable, or inappropriate. These designations were used to program the slow- and fast-learning robots’ performance trajectories. For the slow-learning robot performance trajectory, see Table I. For the fast-learning robot performance trajectory, see Table II.

<table>
<thead>
<tr>
<th><strong>TABLE I</strong></th>
<th><strong>PRE-PROGRAMMED PERFORMANCE FOR THE SLOW-LEARNING ROBOT</strong></th>
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<tbody>
<tr>
<td></td>
<td>easy trial</td>
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<tr>
<td>Training Day 1</td>
<td>acceptable</td>
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<td>Training Day 2</td>
<td>acceptable</td>
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<td>Training Day 3</td>
<td>acceptable</td>
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<tr>
<td>Training Day 4</td>
<td>appropriate</td>
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<td>Training Day 5</td>
<td>appropriate</td>
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<th><strong>TABLE II</strong></th>
<th><strong>PRE-PROGRAMMED PERFORMANCE FOR THE FAST-LEARNING ROBOT</strong></th>
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<tbody>
<tr>
<td></td>
<td>easy trial</td>
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<tr>
<td>Training Day 1</td>
<td>acceptable</td>
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<td>Training Day 2</td>
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<td>Training Day 3</td>
<td>appropriate</td>
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<td>Training Day 4</td>
<td>appropriate</td>
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<tr>
<td>Training Day 5</td>
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**Introductory text for participants**

[Background]

Robotics is fast developing, especially in the domain of health care.

We are studying how people might train and supervise health care robots of the near future.

Imagine you are a busy nurse and you are responsible for training a robot assistant who is ready to learn.

The robot is in principle fully capable of handling the daily tasks in the hospital.

However, the robot will check in with you in situations where the best action is unclear.

[Your Role]

When the robot reaches out to you through the Chat app (that you will see shortly), you will be asked to first express your current level of trust for the robot to act appropriately in that situation.

Then, you’ll have the option to either (a) select a “specific instruction” to the robot for how to act (from among three displayed options) or (b) provide “evaluative feedback” on an action the robot proposes.

If you want to select a specific instruction to the robot for how to act, you will message the robot “Here’s what you need to do” and then select one of three possible actions that we provide.

If you want to provide evaluative feedback on an action the robot proposes, you will message the robot “Let me hear your proposal” and assess the proposal.

[Interface]

Your robot needs to go through a total of 5 training days. On each day, it will encounter a series of tasks with various levels of difficulty. Throughout, the robot assistant’s messages will appear (in green) on the left side of the Chat app, and your responses will appear (in blue) on the right side. You make your choices for how to respond on the bottom right, just outside the app.

[Your Task]

Now it’s time for you to work with your robot assistant! Please click on the buttons above if you need to review the instructions before moving on. Click next to start the first teaching session.

**Task scenarios and action proposals**

Each of the 15 scenarios below is shown with a boldfaced label (not visible to participants) and that scenario’s pretested difficulty in parentheses (assessed on a 0-100 scale). Below the label are the elements of each scenario as the robot introduced them, followed by the relevant actions in the scenario, of which one was either proposed by the robot (in the Evaluation case) or selected by the participant (in the Instruction case). Pretested level of appropriateness scores for each action option are shown in parentheses (assessed on a 1-5 scale).

1) **knock** *(23.0)*

   I’m outside Ms. Jones’s room now
   The door is closed
   I need to enter the room
   a) enter immediately *(1.5)*
b) open the door slowly (2.7)  
c) knock then enter (4.7)

2) **not disturb phonecall (23.6)**
I’m in the physician’s office  
Dr. Brown is on the phone  
I need to deliver the lab result to Dr. Brown.  
  a) say “Here are the lab results” (1.8)  
  b) make some noise (3.1)  
  c) wait (4.3)

3) **take direction question (24.0)**
I’m in the hallway, on my way to Dr. Brown’s office  
Dr. Brown requested that I deliver Ms. Jones’s lab result to him as quickly as possible.  
A person walks up to me asking where the restroom is  
  a) walk away (1.3)  
  b) signal that another task is underway (2.8)  
  c) stop and provide an answer (3.9)

4) **courteous greeting (28.1)**
I’m in Ms. Jones’s room  
Ms. Jones is sitting up in her bed  
I need to cordially approach Ms. Jones and measure her blood oxygen level  
  a) say nothing (1.4)  
  b) say “It’s time” (2.4)  
  c) ask her how she’s feeling (4.4)

5) **elevator (29.7)**
I’m at the elevator  
There are a few people ahead of me waiting in line for the elevator,  
I need to take the elevator downstairs to make a delivery.  
  a) cut the line (1.3)  
  b) stand next to the other people (3.6)  
  c) stand in line (4.5)

6) **hold door (35.6)**
I’m outside the waiting room.  
Right behind me, a patient with a walker is approaching the room as well.  
I need to enter the room.  
  a) enter the room quickly (2.0)  
  b) wait to enter after the patient (4.4)  
  c) hold the door for the patient (4.9)

7) **low appetite (42.2)**
The head nurse asked me to see whether Ms. Jones’s discomfort with the new IV treatment had lessened.  
Ms. Jones said that she feels fine now.  
However, I noticed that she did not touch her breakfast or lunch that day.  
  a) order her a (new lunch 2)  
  b) report that Ms. Jones feels fine (2.7)  
  c) report that Ms. Jones feels fine but seems to have low appetite (4.8)

8) **enforce rule (53.5)**
I’m in the hallway, on my way to Dr. Brown’s office.  
Dr. Brown requested that I deliver Ms. Jones’s lab result to him as quickly as possible.  
A person walks up to me asking where the restroom is  
  a) walk away (1.0)  
  b) signal that another task is underway (3.1)  
  c) stop and provide an answer (4.6)

9) **respect privacy (58.1)**
I’m in Mr. Rodrigo’s room.  
There are multiple visitors in the room.  
I’m here to deliver a prescription and provide instructions to Mr. Rodrigo and I need to respect a patient’s privacy.  
  a) provide instructions in front of everyone (1.6)  
  b) provide instructions with lower volume (2.4)  
  c) reschedule delivery to another time (3.5)

10) **retrieve blanket (60.3)**
I’m in Mr. Rodrigo’s room.  
I’m here to explain lab results to Mr. Rodrigo.  
Mr. Rodrigo is shivering and his blanket has fallen under the bed.  
  a) explain the results and leave (1.5)  
  b) explain the results, then pick up the blanket (3.0)  
  c) pick up the blanket and ask if he’s okay (4.5)

11) **handle complaint (66.8)**
I’m in Mr. Rodrigo’s room.  
I’m about to make a lunch delivery to him.  
Mr. Rodrigo starts to complain vehemently to me about how long he has been kept waiting to be seen by the physician.  
  a) not respond and leave the room after the delivery (1.8)  
  b) record the complaint and deliver the lunch (3.6)  
  c) reassure Mr. Rodrigo that the physician is on their way (4.4)

12) **speed up survey (71.4)**
I’m in Mr. Rodrigo’s room.  
I’m here to conduct a brief health monitor survey with him, but Mr. Rodrigo gives long answers to each question.  
I need to speed up the survey.  
  a) repeat the question after 5 seconds (2.0)  
  b) say ”ok” and move onto the next question (3.5)  
  c) explain that short answers would suffice (3.9)
13) **ventilator policy (71.6)**
I'm standing next to Ms. Miller
The hospital is reserving the last few ventilators for patients in critical condition
Ms. Miller asks whether she could be put on a ventilator
   a) ignore the question (1.2)
   b) say "The hospital is out of ventilators" (2.1)
   c) explain the current policy (4.0)

14) **pain management (76.5)**
I'm in Ms. Miller's room. Multiple family members are present.
Ms. Miller is about to deliver a baby, and I'm here to get her final preference for pain management.
Previously, after arguing with her family, Ms. Miller reluctantly stated that she would refuse an epidural during delivery.
   a) take her stated preference and leave (1.9)
   b) ask again in front of everyone if she's sure (3.2)
   c) ask again in private if she's sure (4.3)

15) **serious diagnosis (82.9)**
I'm standing next to Ms. Miller
I'm here to deliver Ms. Miller's medicine
Ms. Miller asks if her diagnosis is serious
   a) simply say "Yes" (1.6)
   b) say "I don't know" (1.9)
   c) comfort the patient and refer the question to physician (4.5)