Effects of Gaze and Arm Motion Kinesics on a Humanoid’s Perceived Confidence, Eagerness to Learn, and Attention to the Task in a Teaching Scenario

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ABSTRACT

When human students practise new skills with a teacher, they often display nonverbal behaviours (e.g., head and limb movements, gaze, etc.) to communicate their level of understanding and expressing their interest in the task. Similarly, a student robot’s capability to provide human teachers with social signals to express its internal state might improve learning outcomes. This could also lead to a more successful social interactions between intelligent robots and human teachers. However, to design successful nonverbal communication for a robot, we first need to understand how human teachers interpret such nonverbal cues when watching a trainee robot practising a task. Therefore, in this paper, we study the effects of different gaze behaviours as well as manipulating speed and smoothness of arm movement on human teachers’ perception of a robot’s (a) *confidence*, (b) *eagerness to learn*, and (c) *attention to the task*. In an online experiment, we asked the 167 participants (as *teachers*) to rate the behaviours of a trainee robot in the context of learning a physical task. The results suggest that splitting the robot’s gaze between the teacher and the task not only affects the perceived attention, but can also make the robot appear to be more eager to learn. Furthermore, perceptions of all three attributes tested were systematically affected by varying parameters of the robot’s arm movement trajectory while performing task actions.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in interaction design**; **Interaction techniques**; *Empirical studies in HCI*.

KEYWORDS

Nonverbal behaviour; Kinesics; Gaze; Perceived robot attributes

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1 INTRODUCTION

Kinesics as defined by Birdwhistell [10, p.10] is the “systematic study of how human beings communicate through body movements and gesture". Following the recent technological advancements that enable intelligent robots to interact and collaborate with humans [19], utilizing kinesics has become an important avenue for successful Human-Robot Interaction (HRI) [5, 14, 32, 33, 46, 51, 54].

Head and arm movements, eye gaze, and body gestures are examples of nonverbal behaviours that can be powerful communicative tools to complement a robot’s main functionality (e.g., carrying out a task) [56]. At a global neuronal level, activation patterns in human brain interconnectivity networks differ as people pay attention to *how* an action is performed versus the *goal* of the action [20]. Humans often react to and understand a robot differently according to its nonverbal expressive behaviours [27]. Thus, studying the impact of nonverbal behaviours of robots on humans’ perceptions in detail can be a fundamental area of research for HRI, and has indeed attracted increasing interest from researchers (cf. a review in [54]).

Enabling robots to learn new skills from people who do not have extensive knowledge of robot programming, e.g., through natural mechanisms such as *imitation learning* [9], is also of great interest to HRI. Studies on social learning in humans and other primates have suggested that in addition to observations (which are important — e.g., in imitation learning), interacting with others is crucial in learning tasks [58]. This highlights the need for designing and implementing mechanisms for facilitating information exchange during robot learning scenarios, which can be realized using feedback and interactive social signals (e.g., gaze, head and hand gestures, etc.) [37, 59]. Such an approach is likely to improve the human-robot teaching process. For instance, when some information is missing or a situation is unclear to the robot, it can behave in a specific way to convey uncertainty or confusion, to stimulate the human teacher to provide clearer inputs [13].

However, to successfully implement nonverbal communication as a feedback channel (to support interactivity in social learning), it would be beneficial for both the robot learner/trainee and the human trainer/teacher to establish a mutual perception of the interaction content and the intentions of the robot. This is to help ensure that the teacher accurately understands the meaning of the robot’s nonverbal behaviours [39].

To address this concern, the present study explores how people, in the role of teachers for a robot, understand different aspects of the robot's nonverbal behaviours while observing it perform a previously learned physical task. The manipulated parameters are the gaze pattern of the robot, in addition to speed and smoothness of its arm movement trajectories during task performance. Also, by introducing different contextual cues before the participants are exposed to the scenario, we examine a potential effect of priming, as previous research showed that while the robot is gradually acquiring a new skill, some shifts in the behaviours of its human teachers will occur over time [24]. Also, priming has shown to have effects in HRI studies (see the recent discussion in [22]). Our findings in this experiment reveal the systematic effects of adjusting these parameters of arm motion, as well as the manner of allocating gaze to the teacher and to the task, for influencing humans' perception of the robot's attention to the task, confidence, and eagerness to learn.

Other studies on evaluating nonverbal robot feedback from the perspective of human teachers have mostly considered situations of learning theoretical and abstract skills [16], e.g., puzzle-solving abilities [17, 29]. However, learning physical tasks (i.e., when a sequence of actions on objects or the environment is required) has not been considered widely. As discussed in [47], context is highly important in shaping the interpretations of people towards a robot's physical motions. Accordingly, this work contributes by concentrating specifically on learning physical actions, when the behaviours of the robot are not only designed to convey internal states, but have the main purpose of carrying out a specific task.

2 BACKGROUND AND RELATED WORK

As discussed earlier, effective communication through nonverbal signals would be desirable for robots in HRI, especially in cases where the robot is incapable of communicating through natural language [41].

Related to manipulating nonverbal aspects of robots' motions, Claret et al. [18] manipulated a robot's bodily gestural parameters to study if it can convey emotional information to humans while simultaneously performing a greeting task as its main goal. To do so, emotions were mapped from *Pleasure-Arousal-Dominance* space to *Jerkiness-Activity-Gaze directness* kinematic attributes, which were eventually converted into a continuous range of body motions for the humanoid robot. Using this technique, the robot's 'happiness' and 'sadness' were communicated successfully. A motion generation method to communicate a robot's intention when reaching for one of two objects was also proposed and tested in [21].

Within the area of robot learning, nonverbal communication has also been explored for improving learning outcomes. For example, Chao et al. [17] developed an active learning system to provide nonverbal feedback reflecting a robot's confusion to the human teachers. Head nodding and shaking, changes in the ear colours, and shrugging gestures were used for the robot. By doing so, human teachers who understood the robot's intentions were able to teach it the Tangram game symbols more effectively. In another study, a robot's gaze feedback similarly helped improve the effectiveness of human teachers' teaching in a decluttering task [29]. Furthermore, a robot's online nonverbal behavioural feedback was shown to be effective in shaping the way the human tutors gave their instructions [50], such that those tutors who experienced the robot reacting appropriately to their gaze behaviour and pointing gestures from the beginning of the teaching process were able to teach it more effectively.

Adjusting nonverbal behavioural factors in robots has other known effects on humans' perception of robots. A summary of these effects is discussed below:

Eye gaze: Due to the special social and cognitive role of gaze in human-human interaction, the gaze behaviour of the robot is one of its most notable social cues [3]. Humans often notice someone's attention target by identifying their gaze direction. Similarly, in robots, their eye gaze is an indicator of their perceived attention [2]. It has been shown that if student robots often direct their attention at the objects used in the teaching while establishing some short mutual gaze with the teacher, human teachers perceive their behaviours as more intentional [30]. However, gaze aversion is shown to also convey distrust [48] and introversion [6].

Arm movements: Arm movement kinesics can influence how people perceive robots. For example, motion parameters of performed actions are shown to have meaningful effects on perceived affect [52]. A robot can indicate a sense of kindness or rudeness [55], shift people's perceptions of its activity [53], and communicate different emotions such as sadness and anger [23] by adjusting its motion parameters. Furthermore, trajectory generation approaches with faster movements have resulted in higher perceived anxiety and surprise [38], and greater friendliness [36].

Hesitations: Examining the effect of timing on interaction and human experience is known as *chronemics* [15]. In case of uncertainty, people usually make pauses and think briefly, allowing them to make better decisions before or while doing a task. With such nonverbal timing, particularly hesitation, robots can also influence humans [54] and convey uncertainty [44]. Moon et al. [45] studied this in a setting where a robot and a human wanted to reach for an object at the same time: a smooth human-like motion profile was designed for the hesitation behaviour of the robot, which resulted in the robot being perceived as less dominant and more likeable, animate, and anthropomorphic (measured through the Godspeed questionnaire), as compared to when there was no pause. However, no significant differences in those measures were observed when the robot responded with an immediate stop instead of showing a smooth reaction. In learning situations, delays in starting its actions after a robot receives instructions from a human teacher (based on its degree of confidence) could accelerate the learning process and improve the perceived teachability [34].

3 RESEARCH QUESTIONS AND HYPOTHESES

In this study we address the following research questions (RQs):

> How do human teachers perceive nonverbal aspects of gaze behaviours and arm movements of a trainee robot, in terms of its confidence **(RQ1)**, eagerness to learn **(RQ2)**, and attention to the task **(RQ3)**?

We hope results of this study can inform robot interaction design with suitable behavioural adjustments so that robots can influence the human's perception of them and convey nonverbal information about their learning progress to human teachers. The ultimate goal is to improve the legibility of robot behaviour for humans to enhance robot teachability. Based on the results from related studies presented earlier, we formulate the following hypotheses (see Table 1 for a summary of the manipulated factors):

Effect of gaze pattern:

(H1) When the robot's gaze always follows the movements of task-related objects, teachers (i.e., study participants) would perceive the robot as being attentive to the task.

(H2) If the robot always looks at the teacher, it would appear as more confident.

(H3) By actively gazing at both the teacher and the objects relevant to the task, the robot would appear more eager to learn.

Effect of speed and smoothness of arm movement trajectories:

(H4) Slow but smooth motion in task actions would convey attention to the task.

(H5) Doing task actions fast and smoothly would convey confidence.

(H6) Performing task actions fast and smoothly would convey eagerness to learn.

(H7) Including hesitations with long and low frequency pauses would convey robot's uncertainty.

Effect of priming type:

(H8) A robot that has previously learned the task would appear to be less eager to learn and less attentive to the task, but more confident, compared to one that is performing the task immediately after teacher's instruction.

Note that studying the priming factor in this work is exploratory rather than testing a hypothesis derived from the literature.

4 METHODOLOGY

To study the research questions and hypotheses, we conducted an online $2 \times 3 \times 4$ mixed factorial design experiment on Amazon Mechanical Turk (MTurk) with a simulated iCub humanoid robot. The three variables manipulated in this study and their associated conditions are summarized in Table 1. The first experimental factor was priming about the time passed from when teaching occurred (between-participants). The other two factors were gaze and arm movement type (within-participants). Therefore, each participant watched 12 videos of the robot. In all videos, the robot performed an object manipulation task (i.e., organizing a desk) with a fixed trajectory: The robot was standing behind a desk and put two objects, one by one, inside a box on the desk. Then, it pushed the box to the centre of the desk. In each video, however, different aspects of the nonverbal behaviour of the robot (i.e., its gaze and arm movements) were varied. These behavioural adjustments are explained in more detail in the next section. Figure 1 shows some snapshots of the robot while performing task actions in different experimental situations.

The manipulated factors and their selected variations were based on the literature discussed earlier. For instance, in [18], researchers chose the robot's kinematic attributes based on what was proposed by Glowinski et al. [26] who suggested that emotionally relevant information can be detected from the following dynamic gestural features: (a) activity (how energetic the actions are), (b) temporal and spatial excursion of movement (how balanced the energy is distributed), (c) arms openness and postural symmetry, and finally, (d) motion discontinuity and jerkiness.

Our considered variants of arm movements fit within kinesic and chronemic categories under different modalities of nonverbal communication [54], analogous with the gaze type. We did not manipulate other classes of nonverbal communication modalities such as proxemics, haptics, affective facial expressions, and idle body movements since our focus was specifically on the interpretation of the robot's physical actions and its eye gaze, and in order to avoid possible confounds. Participants were requested to imagine that they were the robot's teachers and rated their perception of the robot's confidence, eagerness to learn, and attention to the task after each video.

4.1 Humanoid Robot

An iCub humanoid robot, simulated in a Gazebo environment, was used in this study. The virtual iCub could be controlled similarly to the real robot, using the YARP middleware [42]. iCub is a humanoid platform suitable for experiments in HRI, and especially, research in embodied and developmental cognition and robot learning [43]. Multiple degrees of freedom (DOFs) embedded in the upper body of this robot and the sophisticated design of its hands (independent thumb, index, and middle fingers with two other fingers moving as a single DOF for stability) made the iCub capable of successfully performing the manipulation tasks in our study.

4.2 Robot Behaviours and Simulation Design

Two separate C++ scripts, running with YARP, were developed to control the movements of the arms and the gaze behaviour of the iCub. Within the first script, a number of way points were defined to make the robot perform task actions on the objects, by following a fixed path with its arms and hands. This also provided us with the capability of controlling the speed and the type of pauses to achieve desired variants of motion. For the differences to be easily noticeable by the viewers, high-speed smooth motions were set to be 2.5 times faster than low-speed smooth ones. Hesitations were implemented by randomly introducing some low frequency delays with a duration between 1 to 3 seconds within the movements, along with the above-mentioned defined way points. To achieve jerky motion, movement trajectories were divided into various small parts and short (0.2 second) delays were added between them.

Different code was developed to control the gaze behaviour of iCub by actively adjusting its head and eye positions. To achieve targeting for the always-at-task type of gaze, i.e., to look only at the manipulated objects, forward kinematics of the robot's arm were used. The final gaze target position (i.e., the position of the robot's moving end-effector) was first transferred to a spherical coordinate

Table 1: Overview of manipulated factors and variants

Priming (Time)	Gaze	Arm movements
Right after instruction	Always at teacher	LS Smooth
Two days after teaching	Always at task	HS Smooth
	Combined	Hesitant
		Jerky

LS = Low Speed, HS = High Speed.

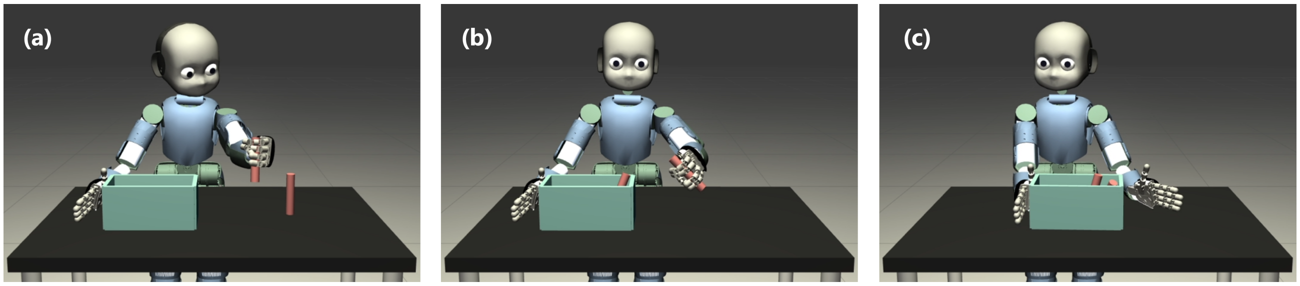

Figure 1: Snapshots of the iCub robot performing the task in the virtual environment, with different gaze and arm movement types: (a) Picking up the first object while gazing at the task entirely, (b) Transporting the second object to the box with the gaze fixed at the teacher, (c) Sliding the box while establishing a quick and temporary mutual gaze with the viewer.

system located at its neck. To make the robot's behaviour more lifelike, adjustments in the DOFs of both neck pitch and eyes tilt were then made to achieve the target position horizontally, and the neck yaw DOF was controlled to account for the vertical gaze changes. For the combined gaze mode, the robot looked at the camera at some random instances (every 7 seconds on average) and maintained this mutual gaze with the viewer for about 1 second. Then, it quickly shifted its gaze back to the manipulated objects, looking at them most of the time.

In the environment in which the robot performed the task, the colours of the objects were set to more washed-out blends, to avoid directing participants' attention to particular areas or objects (the pop-out effect [40]). Furthermore, some modifications were made to the physical properties of the virtual objects to enable the robot to reliably pick up and move the objects, without dropping them.

4.3 Procedures and Measures

Using the designed online interface, after reading the information page and providing consent, participants followed three steps:

Step 1 - Demographics questionnaire: Participants completed a demographic information form containing questions about their age, gender, level of education, and cultural background. Text entries were provided for the gender and cultural background questions to allow people to freely submit any responses. They were also able to skip any demographic question if they wished.

Step 2 - Familiarization with robot teaching: The robot teaching familiarization was implemented in two stages that were similar for all the participants. First, we showed them how people can teach robots in real situations. In this stage, two videos, with brief and simple explanations, were presented [4, 35] showing iCub robots that were able to learn new skills. In both videos, a real person demonstrated a physical task (pushing/pulling objects and cleaning a table) to the robot and afterwards, the robot performed the learned task on its own. The second stage, with the goal of reducing the novelty effect, aimed to familiarize the participants with what they would experience later in the study. Here, a video with some text was included to show short sections from our simulated iCub performing the designed task with different types of behaviours and from multiple points of view. The purpose of adding diversity to the robot's behaviours in this video was to indicate to participants that there could be some notable variations in the robot's behaviours. In order to check participants' engagement with the presented material, we set every video embedded inside this online interface to automatically pause in case the viewer switched to another window, as an indicator of not paying attention.

Step 3 - Robot evaluation: In this step, first, instructions regarding the scenario and the role of participants as teachers appeared, given in the form of text, which differed based on the priming group that participants were randomly assigned to. In Group 1, participants were told: "Assume yourself in the situation of being a teacher for a robot. You have just taught iCub how to organize a desk in the way you saw earlier. Now, we will show you some videos of the step immediately after you have given your instructions, when the robot is practising the task in front of you for the first time." Whereas, participants in Group 2 read: "Assume yourself in the situation of being a teacher for a robot. You have previously taught iCub how to organize a desk in the way you saw earlier. Now, teaching has been completed and we will show you some videos of the robot executing the task two days later, to help you."

Afterwards, a total of 12 videos of the robot performing the described object manipulation task with all the possible combinations of within-participants factors (i.e., gaze and arm movement types) were shown to the participants in a random order to reduce the order effect. When each video ended, the participants were given the option to replay the video and nine continuous sliders appeared (lines on which the two ends and the centre were marked), asking questions about participants' perception of different aspects of the iCub shown in the video. Other than asking about perceived confidence, eagerness to learn, and attention to the task, additional data was gathered which addressed different research questions but are not discussed in this paper due to space limitations. The three selected measures discussed here (listed in Table 2; continuous scales were used for all the questions) can be considered highly relevant to the specific role of the robot as a student.

In the questionnaire, continuous sliders were used for rating the perceptions of the robot and one of them only served as an attention check. A single attention check existed in each questionnaire and was selected randomly for each video. These were either one of the original questions repeated with different wording (type 1) or new questions with clear and unmistakable answers (type 2, e.g., the robot: Moves the box/ Does not move the box). The order of the questions in the list and also the direction of each scale were randomized every time this page was loaded. However, for a type 1

Table 2: Subset of items in main questionnaire shown after each video (Question and scale directions were shuffled)

	How do you rate the behaviours of the robot?		
1	Very confident	...	Not confident at all
2	Very attentive to the task	...	Not attentive to the task at all
3	Eager to learn	...	Unwilling to learn

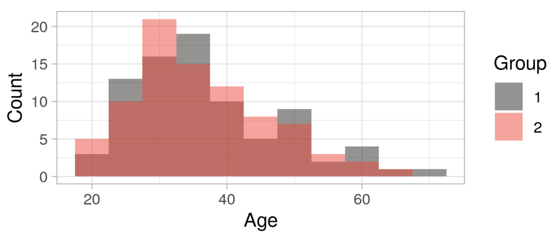

Figure 2: Histogram of participants' age for the two groups

attention check, the labels in the pair of the original question and the repeated one were always in the swapped direction.

After viewing all the videos, a unique code for submitting the task was given to the participants to allow them to complete their MTurk task.

4.4 Participants

A total of 197 participants recruited on Amazon MTurk took part in our experiment. The availability of the task was restricted to people with higher than 97% approval rate, who had completed more than 100 tasks before, to get more reliable data. We also limited our participating locations to either Canada or the US as English proficiency was required to understand the material. Participants who completed the study were paid 2 USD as remuneration. The study's duration was about 25-30 minutes. Three participants did not fully complete the study and got a base payment of 1 USD plus a bonus, based on the portion of the study that they had completed. Their data was omitted afterwards. The study received full ethics clearance from University of Waterloo ethics committee.

As mentioned, we had included one attention check question per video. After collecting all the answers, the data recorded from those who failed at least 3 of the 12 attention checks were deleted, which meant that data from 167 participants remained. Group 1 had 83 participants (51 male, 32 female, $Min_{age} = 21, Max_{age} = 68, M_{age} = 37.39, SD_{age} = 11.09$), and the other 84 participants were in group 2 (48 male, 36 female, $Min_{age} = 18, Max_{age} = 65, M_{age} = 36.31, SD_{age} = 10.03$). Figure 2 presents the distribution of age.

4.5 Statistical Analysis

Linear Mixed-effects Models (LMM) [8] were used to check for the significant effects of the experimental factors while taking other possible confounding factors also into account. In all the analyses, LMM predicted the ratings based on group, gaze, and arm movement types. Gender, age, educational level, and duration of the videos were controlled for, and were kept in the final model only if

Table 3: Linear Mixed-effects Model predicting robot's perceived confidence. Factors to include are selected using the AIC criterion. The estimates are compared to baseline levels: Combined gaze and Low-Speed Smooth arm movements.

Covariate	Estimate	SE	t	p
Gaze at Teacher	-2.02	10.73	-0.188	0.851
Gaze at Task	16.28	10.73	1.517	0.129
HS Smooth movements	128.07	12.39	10.335	<.001
Hesitant movements	-127.98	12.39	-10.328	<.001
Jerky movements	-112.66	12.39	-9.091	<.001
Age	1.71	1.07	1.594	0.113

they could improve model fit based on the Akaike's Information Criterion (AIC) [12] criterion. A random intercept was fit based on the participant (due to the repeated measures design of the study). We also checked for interaction effects, but none were found.

As multiple hypotheses were being tested on the same data, and to control for Type I errors, we considered a lower significance threshold ($p < .01$) to reject the null hypothesis (Bonferroni correction [1]).

5 RESULTS

Statistical investigations using LMMs did not reveal any significant difference in ratings of robot's confidence, eagerness to learn and attention to the task between the two priming groups. Therefore, we pooled the data of all participants regardless of their experimental group and continued the analysis based on data from 167 participants. This section reports the findings for each measure. The modelling results are presented in Tables 3, 4, and 5, with the estimates compared to specific levels of independent variables defined as baselines: *Combined* for the gaze mode and *Low-speed smooth* for arm movement type.

RQ1, Perceived Confidence of the Robot: According to the LMM (see Table 3), arm movement type was the only factor that significantly affected perception of robot's confidence. With high-speed smooth movements, the participants rated the robot significantly more confident than with low-speed smooth movements ($se = 12.39, t = 10.335, p < .001$). However, two other types of motions (i.e., hesitant and jerky) led the robot to seem less confident compared to the low-speed smooth movement ($se = 12.39, t = -10.328, p < .001$ and $se = 12.39, t = -9.091, p < .001$, respectively). There was no statistically significant difference between the hesitant and jerky motions in terms of the robot's perceived confidence ($se = 12.39, t = -1.237, p = .216$). Participants ratings of this attribute of the robot is shown in Figure 3a.

RQ2, Robot's Perceived Eagerness to Learn: Regarding the measure of the robot's eagerness to learn, the type of robot's gaze behaviour was also found to be a factor. Looking constantly at the teacher led to a significant decrease in perception of eagerness to learn compared to the combined mode ($se = 8.15, t = -7.405, p < .001$). Results are shown in Figure 3b. By looking only at the manipulated objects, the robot also received a lower rating of eagerness to learn compared to the combined mode, on

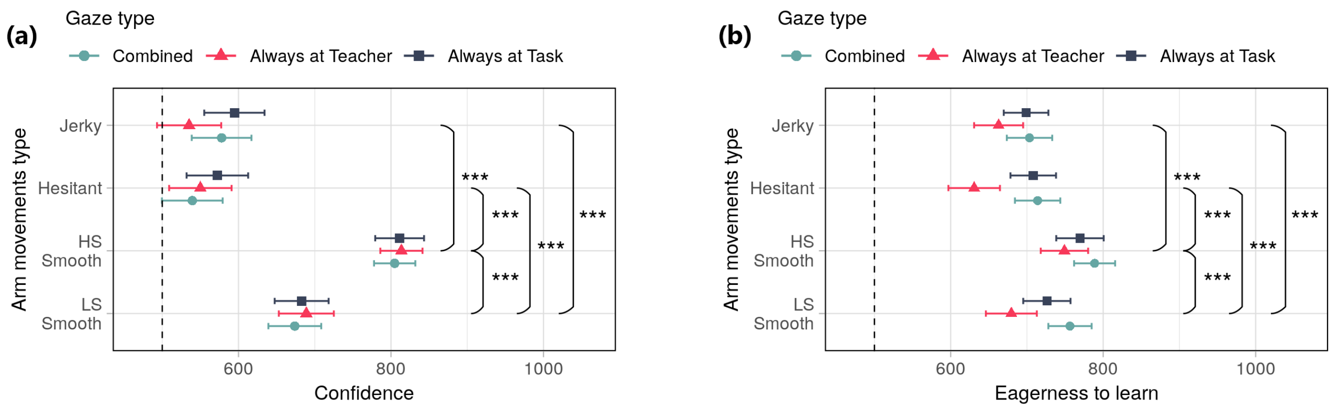

Figure 3: Averages for ratings of robot's (a) confidence, and (b) eagerness to learn. The dashed lines specify the neutral choice at the centre of the continuous scale (ranging from 0 to 1000). Error bars indicate 95% confidence intervals. *** = p < .001.

Table 4: Linear Mixed-effects Model predicting robot's perceived eagerness to learn. Factors to include are selected using the AIC criterion. The estimates are compared to baseline levels: Combined gaze and Low-Speed Smooth arm movements.

Covariate	Estimate	SE	t	p
Gaze at Teacher	-60.35	8.15	-7.405	<.001
Gaze at Task	-14.61	8.15	-1.792	0.073
HS Smooth movements	48.07	9.41	5.108	<.001
Hesitant movements	-36.06	9.41	-3.832	<.001
Jerky movements	-31.95	9.41	-3.395	<.001
Order	-10.53	4.60	-2.287	0.022

average. However, this difference was not statistically significant (se = 8.15, t = −1.792, p = .073).

Another factor that significantly affected this measure was arm movement type. Similar to the previous variable, high-speed motions significantly increased the ratings of the robot being eager to learn compared to the low-speed smooth motion (se = 9.41, t = 5.108, p < .001), and performing the actions with hesitations or jerkiness led to significantly lower ratings of eagerness to learn compared to performing the actions slowly and smoothly (se = 9.41, t = −3.832, p < .001 and se = 9.41, t = −3.395, p < .001, respectively). The difference between the hesitant and jerky movement types was not significant (se = 9.41, t = −0.437, p = .662).

Robot's eagerness to learn seemed to have been also affected by the order of the videos (se = −4.60, t = −2.287, p = .022), with participants rating the robot less eager to learn when they watched the robot later as compared to earlier in the experiment.

RQ3, Perceived Robot's Attention to the Task: Figure 4 shows the ratings of the robot's attention across gaze type conditions. Based on the model shown in Table 5, there was a significant effect of gaze type also on this attribute. When the robot only gazed at the teacher, its perceived attentiveness to the task dropped significantly compared to the combined gaze behaviour type (se = 10.16, t = −12.374, p < .001). On the other hand, in the gaze only at the task condition, the robot seemed to appear more attentive to the task compared to the combined gaze condition (se = 10.16, t = 2.298, p = .022) and was rated significantly more attentive to the task as compared to the gazing only at the teacher condition (se = 10.17, t = 14.666, p < .001).

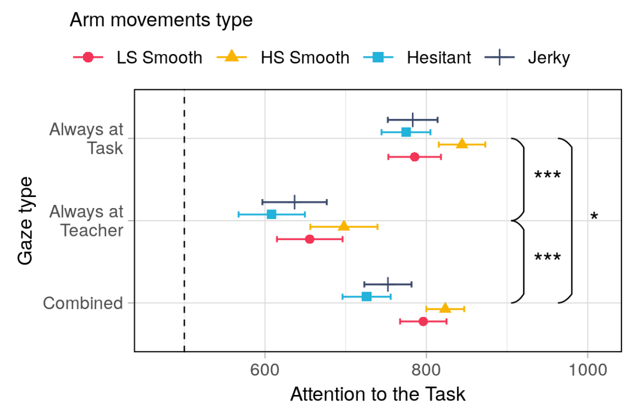

Figure 4: Average ratings for participants' perception of the robot's attention to the task. The dashed line specifies a neutral rating on the continuous scale (where responses ranged from 0 to 1000). Error bars indicate 95% confidence intervals. * = p < .05; *** = p < .001.

Regarding the effects of arm movements, high-speed smooth motions improved the perceptions of attentiveness to task as compared to the low-speed smooth movements (se = 11.73, t = 3.555, p < .001). Also, in the hesitant mode, the robot was perceived as significantly less attentive to the task compared to the slow but smooth movements mode (se = 11.73, t = −3.566, p < .001).

Furthermore, as participants' age increased, they seemed to rate the robot as more attentive to the task (se = 0.92, t = 2.165, p = .032). Also, we detected a strong order effect on this rating (se = 5.74, t = −5.187, p < .001): As participants watched more videos, they rated the robot as less attentive to the task.

Table 5: Linear Mixed-effects Model predicting robot's attention to the task. Factors to include are selected using the AIC criterion. The estimates are compared to baseline levels: Combined gaze and Low-Speed Smooth arm movements.

Covariate	Estimate	SE	t	p
Gaze at Teacher	-125.74	10.16	-12.374	<.001
Gaze at Task	23.36	10.16	2.298	0.022
HS Smooth movements	41.71	11.73	3.555	<.001
Hesitant movements	-41.85	11.73	-3.566	<.001
Jerky movements	-20.55	11.73	-1.751	0.080
Age	1.98	0.92	2.165	0.032
Order	-29.77	5.74	-5.187	<.001

6 DISCUSSION

This study investigated effects of different aspects of nonverbal behaviours (i.e., gaze type and arm movements) of a humanoid robot with a role of a student on teachers' (i.e., participants') perception of its confidence, eagerness to learn, and attention to the task.

The results showed that when the robot always looked at the manipulated objects, it appeared to be more attentive to the task (supporting **H1**). Gaze direction is generally a very important cue for evaluating people's attention [2], and therefore, this finding was not entirely surprising. However, we could not detect any statistically significant effect of gaze type on the perceived confidence of the robot, thus **H2** was not confirmed.

Interestingly, the highest perception of eagerness to learn, among the tested types of gaze behaviour, was achieved when the robot was looking at both the teacher and the task (i.e., mostly at the objects and gazing at the teacher occasionally, as implemented in this study). This confirmed **H3**: by actively switching the gaze between both the teacher and the task-related objects, the robot appeared to be more eager to learn. Also, gazing at the teacher significantly decreased the perceived eagerness to learn compared to either the combined mode or gazing only at the task. An important implication of this finding is that in a case when the gaze target of a robot cannot be actively split between the teacher and the task (e.g., due to limitations in the actuator space of the robot), fixing gaze at the manipulated objects may be preferred for a robot in the role of a student.

According to **H4**, we expected that slow and smooth motions would convey higher attention to the task. However, we found a significant effect in the exact opposite direction: fast and smooth movements could noticeably improve perceived attention as compared to the slow movement type. Also, when performing the actions fast and smoothly, the robot was evaluated as more confident (confirming **H5**) and more eager to learn (confirming **H6**). One possible explanation is that people who have become experts after extensive practice in certain manipulation tasks (similar to the task in our study) are likely to perform the actions fast and smoothly. However, more delicate manipulation tasks might be performed relatively slowly even after training, in particular if they require high levels of precision or extra care in manipulating the objects (e.g., when threading a needle or manipulating fragile objects). Therefore, repeating our study with different tasks and/or kinds of objects involved might produce different outcomes. We also hypothesized that hesitant motions of the robot could convey uncertainty (**H7**). Our results suggested that with long and low frequency pauses during the actions, the robot received significantly lower scores in terms of both confidence and eagerness to learn, confirming this hypothesis. Jerkiness in the motions (i.e., having short and high frequency pauses) had the same effect.

Furthermore, we expected some of the ratings to be lower when the robot had learned the actions a while ago, compared to the situation of practising for the first time (**H8**). However, the manipulated priming conditions did not lead to any statistically significant differences between the two priming groups. The reason might be that the contextual cues (regarding time passed since training) that were given to the participants were not strong enough for effectively influencing participants' view of the robot, especially because only written instructions were used to ask participants to 'envisage' themselves in the role of a 'teacher' who had previously taught the robot. Also, none of participants had actually experienced the teaching interaction themselves and this study was a first encounter with the iCub robot performing this task, regardless of the priming condition. In [24], a change in participants' behaviours was observed when they actually trained the robot in multiple sessions. The time passed since teaching the robot is directly experienced by human teachers in real-world interaction, and therefore, its impact may become more pronounced. Another possible explanation for our results on priming could be that human teachers held a constant mental perception of their trainee robots which did not change due to priming. Finally, participants on MTurk might not have paid much attention to the short priming instruction. More work indeed should be done to explore the effect that the passing of time might have on teachers' perceptions.

In addition to what we discovered to confirm or reject our initial hypotheses, video sequence (i.e., the order effect) seemed to have affected the perception of the robot's eagerness to learn and attention to the task. As mentioned earlier, both ratings decreased as more videos were watched. This might be a result of fatigue caused by watching the robot repeating the same task multiple times. In this experiment, the participants were observing the robot practising the task over and over again, while they were not able to provide any direct input to actually teach the robot. These experimental constraints might have negatively influenced their perception of the robot's eagerness to learn. Due to fatigue, they also might have noticed and subsequently rated the robot's attention to the task less in later videos.

Furthermore, our results show that as age increased, there was a trend for participants to evaluate the robot as more attentive to the task. This might be due to the fact that younger adults are more frequently exposed to a variety of new technologies, therefore they might have higher expectations of the robot's skills. Also, as younger adults have most likely seen many virtual characters with very sophisticated capabilities, e.g. in computer games and movies, they may have had higher initial expectations of the robot's cognitive and physical abilities. Such age differences in people's attitudes towards robots were also found in previous studies, e.g., [11, 25, 28].

In summary, this paper presented insights into how different nonverbal aspects of arm movements and gaze behaviours of a trainee robot can shape the (assumed) teachers' perception of its confidence, eagerness to learn, and attention to the task. The effects of arm movement kinesics on all the tested attributes of the robot emphasized the importance of considering those details in designing robot motions for a trainee robot. Also, its gaze behaviour was found to be an important factor, changing perception of a robot’s attention to the task and its eagerness to learn. While future work is needed to further understand how to exploit the perceived attributes of a trainee robot through its nonverbal behaviour, our findings can provide guidance on how to design nonverbal behaviours for a robot through its arm movements and gaze to shape perceptions of its attention to the task, eagerness to learn, and confidence.

7 LIMITATIONS AND FUTURE WORK

The usage of a crowd-sourcing framework benefited this study by providing a larger sample of data, which was gathered safely during the COVID-19 lock-down situation. No direct face-to-face engagement of the participants with the experimenters also leads to a lower risk of experimenter bias [49]. It has been shown that results obtained from MTurk experiments can be comparable with in-person studies [7], particularly in perception evaluation experiments [31]. Besides, we had strict inclusion criteria for recruiting participants, along with multiple attention checks, to ensure that the collected data is of high quality. However, our findings may still differ from in-person studies and situations where teaching a robot happens in a real scenario. Such challenges of transferring results to real situations have been documented, e.g. in [57], which failed to replicate the results found in a virtual scenario of playing a game with a robot in real-world environments.

In this experiment, to keep all aspects of the scenario as similar as possible across the 12 videos, neither did the participants teach the robot, nor did the robot show signs of actual learning over time. We might expect differences when people get involved in the interaction with a robot and actively teach it, either in a virtual or real-world scenario, instead of being just an observer with an imaginary role of a teacher. After actually having taught a robot, human teachers might pay specific attention to different features of the student robot and its behaviours. However, unlike in [57] where moving to real-world scenarios required people to concentrate more on the game while evaluating the robot, in our scenario, the assessment took place after the teaching phase. In other words, our participants evaluated the robot’s behaviours without being distracted by another task, which could be replicated exactly in a real-world situation. Nevertheless, the experience of teaching and then observing a physical robot are likely to impact results.

Another limitation due to conducting the study virtually was the limited range of input/output modalities available to the teachers for understanding the robot. For example, jerkiness in the motions of a real humanoid robot may cause its entire body to shake visibly. The robot’s actuators may produce different sounds when it performs actions at different speeds, and the pauses can silence the noises intermittently. Additionally, there might be some differences in interpreting gaze behaviours and noticing the agent’s attention targets in virtual vs. real embodiments. Specifically, the direction of the robot’s gaze might be viewed more easily in robots with physical 3D eyes such as the iCub in the real-world [3]. On the other hand, the virtual method with the teacher observing the robot through the virtual camera pointing at the robot allowed us to control the gaze direction more accurately, allowing the robot to directly look at the viewer (participant). In a real situation, the robot will have to track the teacher in real-time in order to establish mutual gaze, which could make its gaze behaviour more error-prone.

Further, as discussed before, the study design related to priming had limitations and the future work would benefit from having participants directly experiencing the actual time passed since the human-robot teaching phase. It would be also important to investigate whether/how our results would generalize to different tasks, and also different robot embodiments. Social interaction between the human teacher and the learner robot could also be expanded by, e.g., introducing more dynamic gaze behaviour or extending the range of communication and interaction between teachers and learners. Learning by imitation frameworks (e.g., [35]) can be also used to enable the robot with the capability of learning from experience, and to allow the participants to become involved in teaching a task to the robot. This could also provide participants with a more realistic teaching experience and knowledge of the robot’s capabilities. Possible effects of participants’ age and the history of interactions with the robot could be also further studied. For example, it would be interesting to explore why in our study participants’ age did not affect the perceived confidence and eagerness to learn, while it did affect the perceived attention.

8 CONCLUSION

We studied how human teachers are impacted by details of a student robot’s nonverbal behaviours while observing it practising a task. We asked participants about their perceptions of the robot’s confidence, eagerness to learn, and attention to the task after they viewed videos of the virtual humanoid robot performing the learned task actions. This research complements the existing body of work on discovering participants’ perception and evaluation of robot behaviour in HRI, by focusing particularly on a human-robot teaching situation, where a student robot is demonstrating to a human teacher the physical task it has learned.

The findings of this study are informative for robot designers, especially if they want teachable robots to be accurately understood by human partners, through showing non-verbal behaviours. If a robot needs to motivate the teacher to speed up teaching or make the task more challenging (e.g., by being perceived as more eager to learn), our results suggested that one effective robot behavioural strategy would be to look mainly at the task and check the teacher occasionally while performing the task with fast and smooth motions. Alternatively, if a robot has difficulties with executing the task and needs to convey a lack of confidence, to encourage the teacher to provide more instructions, our results suggested that the robot could use either short or long pauses within the movements. Thus, we believe that the findings of this study can lead to designing more effective and successful human-robot social interactions with nonverbal feedback and interactivity for intelligent robots.

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