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Autonomous Robot-mediated Imitation Learning for Children with Autism

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Abstract— **Autism Spectrum Disorders (ASD) impact 1 in 88 children in the United States. The cost of ASD intervention is tremendous with huge individual and social consequences. In recent years, robotic systems have been introduced with considerable success for ASD intervention because of their potential to engage children with ASD. In this work, we present a novel closed-loop autonomous robotic system for imitation skill learning for ASD intervention. Children with ASD show powerful impairment in imitation, which has been associated with a host of neurodevelopmental and learning challenges over time. The presented robotic system offers dynamic, adaptive and autonomous interaction for learning of imitation skills with real-time performance evaluation and feedback. The system has been tested in a user study with young children with ASD and typically developing (TD) control sample. Further, the performance of the system was compared with that of a human therapist in the user study. The results demonstrate that the developed robotic system is well-tolerated by the target population, engaged the children with ASD more than a human therapist, and produced performances that were relatively better than that of a human therapist.**

I. Introduction

Autism Spectrum Disorders (ASD) are characterized by difficulties in social communication as well as repetitive and atypical patterns of behavior [1]. According to the report by the Centers for Disease Control and Prevention (CDC), an estimated 1 in 88 children and an estimated 1 out of 54 boys in the United States have ASD[2]. ASD is associated with enormous individual, familial, and social cost across the lifespan [3]. The cumulative ASD literature suggests earlier and more intensive behavioral interventions are efficacious for many children [4]. However, many families and service systems struggle to provide intensive and comprehensive evidence-based early intervention due to extreme resource limitations [5, 6]. As such, there is an urgent need for more efficacious treatments whose realistic application will yield more substantial impact on the neurodevelopmental trajectories of young children with ASD within resource strained environments.

Robotic technology appears particularly promising for potential application to ASD intervention [7-14]. In this work, we design and test a new *co-robotic intervention platform and environment specifically designed to accelerate improvements in imitation skills.* Children with ASD show powerful impairments in imitation with such deficits associated with a host of neurodevelopmental and learning challenges over time[15]. As such, a number of researchers propose imitation skills as critical targets for intervention aimed at ameliorating core features of ASD and as a methodology for enhanced learning outcomes across many other skill domains.

Attempts to teach imitation from both highly structured [16, 17], as well as naturalistic responsive imitation platforms [18], have demonstrated the capacity for within treatment and generalized improvements in terms of both basic imitation as well as collateral social communication skills. Unfortunately, these protocols have often relied on high intensity interventions delivered by limited expert providers across substantial periods of time. In this paper, we design and test the value of a closed-loop robotic interaction system that could potentially impact similar core areas of deficit via intensive responsive reinforcement and specific intrinsically meaningful reinforcement of imitated communicative gestures.

Several research groups have studied robot-assisted imitation learning for children with autism. Robins et al.[19] used a remotely-operated humanoid robotic doll to investigate imitation learning skills in children with autism. Kozima et al.[20] developed a creature-like robot "Keepon" for ASD intervention in younger children. Duquette et al. [21] developed a mobile robot "Tito" and Ferrari et al. [22] built a non-humanoid robot "IROMEC" for imitation learning for children with ASD. While these and other important studies have established the potential benefit of robot-assisted imitation for ASD intervention, there exists significant opportunities for further contributions. In particular, most of these robotic systems are either remotely operated or open-loop systems and thus are not capable of autonomous adaptation to address intervention need. The gesture analysis portion of these tasks has generally been performed via offline video coding of experimental data. In this context, Fujimoto et al.[23] developed a robotic system which could mimic and evaluate child's motion in real-time. However, the participants had to wear a sensorized long-sleeved T-shirt, and they reported that some children did not tolerate it. Feil-Seifer et al.[24], and Greczek et al.[25] introduced Graded Cueing to guide the robot intervention on imitation study for school age children with autism. In this work, however, we are more interested in robot intervention for young children of 3-5 years' of age.

The first contribution of the present work is to develop a robot-mediated learning system for imitation intervention in

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young children with ASD that provides: i) dynamic, adaptive and autonomous interaction without the use of a Wizard of Oz human control system; ii) a non-invasive set-up for the participating child; iii) real-time performance evaluation and feedback; and iv) realized capability for providing detailed performance comparisons between robot and human therapist. **The second contribution** is to conduct a user study of the system with young children with ASD and typically developing (TD) control sample and present comparative results between a robot and a human administrator.

The rest of the paper is organized is as follows. Section II describes the system architecture, system components, gesture recognition and user interface. Section III presents the details of a user study that evaluates the system. The results and implications are discussed in Section IV.

II. System Architecture

The robot-mediated imitation skill learning system (Fig.1) consists of a humanoid robot, NAO [26], and a Microsoft Kinect [27] motion sensing module, both of which are integrated with a supervisory controller (SC) for real-time closed-loop interaction. The Kinect system is placed in front of the participant for gesture recognition. The SC in this case first instructs the robot to show a target gesture to the child. Once the gesture is completed, the child is asked by the robot to imitate the gesture. The SC continuously monitors the Kinect and determines whether the child's imitative attempt falls within a movement band deemed as 'sufficient'. This 'sufficiency' is modifiable to scaffold learning toward more optimal or complete performance of the target gesture. Based on the performance, the SC may instruct the robot either to move towards another gesture or aid the child with reinforcement components and approximations of the gestures within their motor movements. The SC continues this procedure in a closed-loop manner for a specified duration of time and collects data to evaluate the efficacy of the trials towards optimal performance of specific gestures. The SC also instructs the robot to give appropriate rewards and encouragement to the child. A Graphical User Interface (GUI) is designed to administer the tasks, modify task parameters when needed, and record data from experiments.

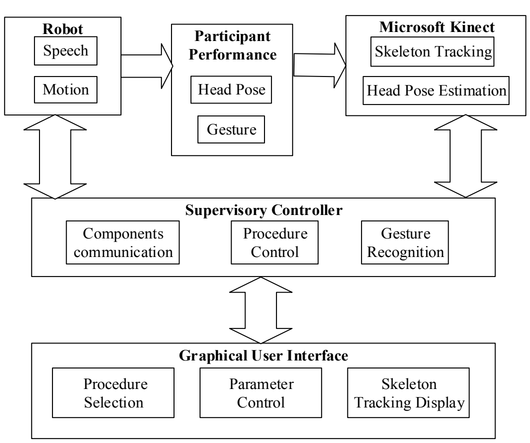


Figure 1. System architecture

A. The Humanoid Robot

Use of a humanoid robot affords for approximation of highly relevant and meaningful human behaviors with ultimate hope that such approximation will enhance generalization [19]. We choose NAO, a medium child-sized humanoid robot (58 cm, 4.3 kg) with 25 degrees of freedom (DOF) for our architecture. We explicitly acknowledge that NAO is not without limitations, including: it cannot control its eye gaze relative to its head and thus head turn is approximated as gaze, and it has other software and system limits as manufactured that necessitate augmentation for more flexible use. Despite these limitations, we choose NAO because of ease of use, sufficient expressive power for intervention tasks, and above all its open architecture that allows relatively easy pathways for custom software development and integration with other devices.

B. Motion Sensing

We used the Microsoft Kinect and its SDK for robust skeleton tracking to get joints positions in the Kinect frame (Fig.2 (a)). In this study, we used joint coordinates of right and left arm wrist, elbow, and shoulder. Skeleton data were processed using a Holt double exponential smoothing filter to avoid glitch and jitter.

Kinect 3D face tracking functions fit a 3D convex mesh on participant's head and output X, Y, Z direction rotation angle in Kinect frame. The head pose was used for estimating the participant's attention on the robot and the human therapist. Participants were seated facing the Kinect. The distance between participant's head and the Kinect was approximately 1.5m; and the distance between the participant and the robot or human therapist was about 2m.

C. Gesture Selection, Mapping and Recognition

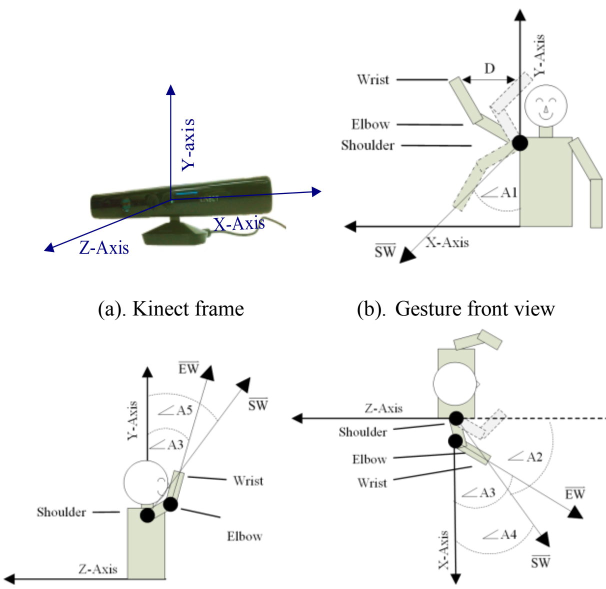
Four gestural movements were chosen for this study: 1) raising one hand; 2) raising two hands; 3) waving; and 4) reaching arms out to the side. These four gestures were intentionally selected due to the low motor skill requirements they presented to participating children (e.g., to ensure focus on imitation skills rather than gross motor abilities) as well as to avoid motor limitations of the humanoid robot.

To map a participant's gesture, each frame's skeleton data (30 frames per second) were transferred to the robot and displayed by the robot in real-time in robot mirroring a child's gesture. Joints detected by Kinect were mapped to the same robot joints. When a joint position was out of robot's workspace, the corresponding robot joint was moved to the nearest boundary of its work space.

This study was designed for 3-5 years' old children. Neither TD children nor children with ASD in this age range can, in general, repeat a specific gesture multiple times in a precise manner. Therefore, to get enough training data for statistical model-based gesture recognition methods was not attempted. Besides, those methods may not be appropriate for providing qualitative feedback regarding the quality of imitated gestures, which is what we want during intervention. As a result, we designed a model-free rule-based gesture recognition method that can provide fast and accurate recognition and qualitative performance feedback to the participant. In order to capture a gesture that can vary in speed among participants, we defined 5 sliding time windows (updated at every frame) ranging from 1s to 5s so that any gesture completed within 5s would be captured.

A correct gesture is defined by a sequence of trajectory constrains (TC) under precondition (PC). PC describes the basic regional constraints of the gesture and the basic joint positional relations. Therefore, the gesture recognition has two steps: precondition estimation and trajectory grading. A correct gesture is $gesture = \{TC_{gesture} = ture \mid s \in PC_{gesture}\}$, where s is arm joints coordinates set.

Fig.2 (b)-(d) show participant's views considering movements of the right arm as an example. The solid lined arm indicates the current arm position; the dash lined arm indicates previous arm position, and dash lined light color arm indicates final arm position. The figures only show angles and distances for the right arm for clarity. Table I lists all the angles and distances in Kinect frame required for gesture definition and recognition.



(a). Kinect frame (b). Gesture front view

(c). Gesture right side view (d). Gesture top view

Figure 2. Kinect frame and participant's gesture view

T_{ang1}, T_{ang2}, T_{ang3}, T_{up1}, T_{up2}, T_{x-dis} were chosen to be π, π, $\pi/2$, 20cm, 10cm, 20cm, respectively. These values can be adjusted through the GUI to make the task easier or more difficult. A gesture is graded positive if the skeleton trajectory satisfies PC, otherwise it is graded as 0. For gestures raising one hand and waving, a correct gesture can be accomplished by either a right or a left hand. For gestures raising two hands and reach arms out, both hands have to satisfy all the TCs. For gestures with one hand, if the gesture satisfies the first *n* TCs, it is graded as $n \times 10/\text{number of } TC$; for gesture with two hands, the grades for two hands are averaged as the final score. The correct gesture got a score of 10.

1) Waving

$$PC_{Wave} = \{\angle A1 < T_{ang1}, \angle A2 < T_{ang2}, W_y > S_y, \angle A3 < T_{ang3}\} \quad (1)$$

$\angle A1 < T_{ang1}$ implies the gesture is started from raising the arm from a lower position; $\angle A2 < T_{ang2}$ indicates wave is in front of the body instead of side; $W_y > S_y$ indicates wrist is higher than shoulder; $\angle A3 < T_{ang3}$ means the forearm remains relatively parallel to the XY plane.

TABLE I. GESTURE VARIABLES

Symbol	Definition
$\overrightarrow{SW}$	Vector pointing from shoulder to wrist
$\overrightarrow{EW}$	Vector pointing from elbow to wrist
W_y	Y coordinate of wrist joint
E_y	Y coordinate of elbow joint
S_y	Y coordinate of shoulder joint
$\angle A1$	Angle between $\overrightarrow{SW}$ and negative Y axis
$\angle A2$	Angle between $\overrightarrow{SW}$ and YZ plane, when $\overrightarrow{SW}$ in negative z direction (arm pointing forward)
$\angle A3$	Angle between $\overrightarrow{EW}$ and XY plane
$\angle A4$	Angle between $\overrightarrow{SW}$ and positive X axis for right arm, angle between $\overrightarrow{SW}$ and negative X axis for left arm.
$\angle A5$	Angle between $\overrightarrow{SW}$ and XY plane, $\overrightarrow{SW}$ with positive X direction for right arm, and with negative X direction for left arm.
$\angle WES$	Angle between upper arm and forearm
T_X	Threshold for angle or distance X
D	X direction movement
$(relation)_{xf}$	Relation in parentheses should be held for x consecutive frames

$$TC_{Wave} = \{(W_y > E_y)_{10f} \text{ \& Upward Movement>} T_{up}, (E_y > S_y)_{10f}, (\text{Only One Hand})_{7f}, D > T_{dis} \text{ in one direction}, D > T_{dis} \text{ in both direction}, TC_{Wave4} \,\&\, TC_{Wave5}\} \quad (2)$$

Upward Movement>T_{up} means hand upward movement is larger than T_{up}, TC_{Wave4} & TC_{Wave5} means the fourth and fifth condition in TC_{Wave} are satisfied at the same time. Those constraints indicate a wave should last for a reasonable amount of time, with only one hand, and will be side by side long enough with a curve shape.

2) Raising one hand and raising two hands

$$PC_{RaiseHand(s)} = \{\angle A1 < T_{ang3}, \angle A2 < T_{ang2}\} \quad (3)$$

$$TC_{RaiseHand(s)} = \{(W_y > E_y)_{10f} \,\&\, \text{Upward Movement}>T_{up1}, (E_y > S_y \,\&\, \angle WES > \frac{\pi}{2})_{10f}, (\angle WES > \frac{3\pi}{4} \,\&\, (\pi - \angle A1) < \frac{\pi}{6})_{10f}, (\text{Only One Hand (one hand raise gesture)})_{10f}, (D<T_{x-dis})_{10f}\} \quad (4)$$

Those constraints indicates only one hand is raised high for one hand raise gesture. For two hands raise gesture, both hands are raised high until the arms are straight out vertically. In both gestures, hand(s) should be held for a while.

3) Reaching arms out to the side

$$PC_{ReachArmsOut} = \{\angle A1 < T_{ang3}, \angle A4 < T_{ang3}, \angle A5 < T_{ang2}, \overrightarrow{SW}.y < 0, (\overrightarrow{SW}.x > 0 \text{ (right arm) or } \overrightarrow{SW}.x < 0 \text{ (left arm)})\} \quad (5)$$

$\angle A4 < T_{ang3} \bigcup \angle A5 < T_{ang2}$ indicates the arm go toward XY plane and stretch out approximately along X axis. The very last condition indicates the arms should start from a lower position.

$$TR_{ReachRamsOut} = \{(\angle A1 > T_{ang1})_{10f} \,\&\, \text{Upward Movement}>T_{up2}, (\angle A4 > T_{ang2})_{10f}, (\angle WES > T_{ang3})_{10f}\} \quad (6)$$

The above equation means arms should be raised from lower positions and from the side of the body and then stretched out evenly side-wise.

In order to validate the gesture recognition algorithm, we performed a small pilot study. Seven adults and 3 TD children participated in an experiment where each participant sat facing the Kinect at a distance approximately 1.5m away from it. Each participant made each of the 4 gestures 10 times. They were instructed to slightly shift their front facing postures between gesturing to create a naturalistic condition. As the participants made the gestures, the gesture recognition algorithm classified them into one of the four categories or a "not recognized" category. These recognition results were compared with the subjective ratings of a therapist. The gesture recognition algorithm was remarkably accurate (> 98%). In the few cases where it failed, it was mostly due to the failing of Kinect to track the participant primarily due to shift in postures.

III. USER STUDY

Fig.3 illustrates the experiment room set-up. An assessment room and observation room were divided by a sound-proof wall and a one-way mirror for observation. The assessment room consisted of a participant chair, Microsoft Kinect, a seat for robot/human therapist, and a projector. In human therapist trials, a projector displayed instructions on the wall behind the participant's chair. The observation room allowed the system operator to initiate and observe the session via a centralized controller and monitoring station.

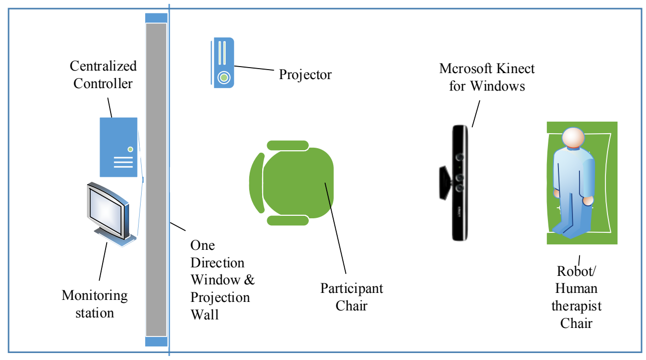


Figure 3. Experiment room setup

A. Participants

Five children with ASD (age in years m = 3.93, SD = 0.68) and five typically developing children (age, m = 3.88, SD = 0.39) participated in the study. All children in the ASD group had received a clinical diagnosis of ASD based on DSM-IV-TR criteria from a licensed psychologist, met the spectrum cut-off of the autism diagnostic observation schedule (ADOS) and had existing data regarding cognitive abilities in the registry. Parents of children in the ASD and non-ASD group completed both the Social Communication Questionnaire (SCQ) and the Social Responsiveness Scale (SRS) to index current ASD symptoms (see Table II.)

TABLE II. PARTICIPANT GROUP CHARACTERISTCS

	ADOS Raw Score	**ADOS Severity Score**	**SRS-2 Raw Score**	**SRS-2 T score**	**SCQ Lifetime Total Score**	**IQ**	**Age**
ASD_M	20.00	7.80	97.80	78.20	17.00	70.60	3.93
ASD_SD	7.41	2.05	31.96	13.90	7.25	26.89	0.68
TD-M	NA	NA	28.40	48.60	3.80	NA	3.88
TD-SD	NA	NA	11.91	5.41	2.39	NA	0.39

B. Task and Protocol

Each child participated in two human-administered sub-sessions and two robot-administered sub-sessions. Each sub-session tested two gestures. All four gestures were exhaustively tested in a randomized order. We compared participant's performance between the robot sessions and the human sessions for: 1) imitation of gesture for each trial; and 2) participant's attention toward robot and human therapist.

Prior to the demonstration of each gesture, the robot and human therapist initiated a robot/human mirroring children gesture part with the verbal prompt "Let's play! I will copy you!" This part lasted for 15s to get the participant involved in the "game". Next, as shown in Fig. 4, is the "child copy robot/human" part. Participant performance and attention data were collected in this part.

In Trial1, the robot or human therapist gave the verbal prompt "Okay! Now you copy me. Look at what I am doing!", demonstrated the gesture twice, and provided the verbal prompt "You do it!" Gesture recognition was initiated immediately upon gesture demonstration and ended 5 seconds following the second full demonstration of the gesture. If the child correctly imitated the gesture, the system recorded full score, and provided praise. If the child did not correctly imitate the gesture, the system provided feedback on the approximation if applicable, and recorded the best score that the participant got. For example, for wave gesture, if the participant just raised and held the hand, then the robot will give feedback "wave side by side!". Trial2A was the same as gesture Trial1 if correct gesture detected in Trial1; Or Trial2A gave a second prompt of the gesture, followed by the verbal prompt "You do it!", and was set up as a gesture + mirroring trial. Here robot mirrored participant's motion during his/her response to help the participant understand what he/she was doing.

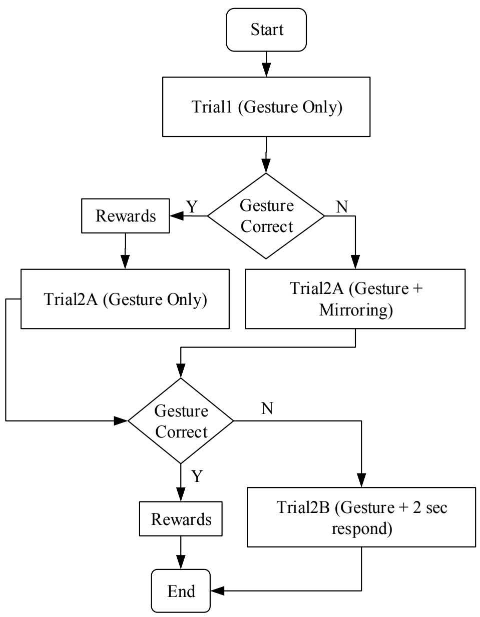


Figure 4. Flow of "child copy robot/human" part

If the child demonstrated the correct gesture in Trial2A, a reward was provided and the session was finished. If unsuccessful, Trial2B was provided with another gesture prompt and the participant was given an extra 2 seconds following the robot gesture to respond. All time constraints discussed above could be adjusted via the GUI to make the tasks easier or harder.

In the human therapist administered sub-sessions, the human replicated robot-administered trials. The flow controls were completed by the system centralized controller and human therapist followed instructions projected on the wall behind the participant. Therefore, the human therapist could fully match the timing and presentation of the robot-administered trials, while still maintaining eye contact with the child seated between her and the projected instructions.

Head pose is a coarse indicator of people's attention via approximation of eye gaze. We used a 85.77 cm × 102.42 cm box around the robot and the upper body of human therapist as the target attention region (robot's height is similar to human therapist's upper body height). Here we assumed that the participant's head orientated to this box represented his attention on the robot or the human therapist.

C. Results

We present two sets of results from the user study to show the effectiveness of the presented robotic system. First, we analyzed direct attention towards the administrator between the robotic and human led trials. This is an important indicator since attention to the administrator is a marker for eventual learning and success within intervention paradigms. Table III shows a group-wise comparison between ASD and TD.

TABLE III. ATTENTION STATISTICAL RESULTS

Group		Robot session			Human session		
		Attention on target time(s)	**Total session time(s)**	**Ratio (%)**	**Attention on target time(s)**	**Total session time(s)**	**Ratio (%)**
ASD	**M**	59.24	96.48	60	41.73	98.53	42
	SD	26.94	26.91	21	24.76	28.32	20
TD	**M**	70.14	101.16	70	47.77	81.23	70
	SD	26.52	29.35	18	15.80	33.32	30

The ASD group spent 18% more time attending to the robot as compared to the human therapist across trials, while TD group paid equal attention to robot and human therapist. Also note that the ASD group required similar amount of time to complete the tasks within trials across robot and human therapists, while TD group spent more time to complete the robot trials. However, note that two-sided Wilcoxon rank sum test results showed that there was no statistically significant difference between attention paid to the robot and human administrator for either group ($p = 0.05$ for ASD and $p = 0.71$ for TD) although the ASD group was much closer to having a statistical difference.

Next we examined the actual demonstrated imitation skills between the human and robot administrator conditions. In order to evaluate participant's performance, every gesture was scored along a scale from 0 to 10 based on the components of the target skill demonstrated allowing us to evaluate not just binary success (e.g., correct/incorrect), but partial success and approximations towards the desired target imitative skill. Table IV shows the group performance between ASD and TD. As expected, given impairments in imitation representing a core symptom of ASD, results indicate that TD children were more successful than ASD children imitating the target gestures across both conditions and did not demonstrate differences in performance between the robot and human conditions. Importantly, within the ASD group, children were far more successful imitating the target gestures during the robot session than in the human session. On an individual level, 3 out of the 5 children indicated better performance in the robot condition with the other two children demonstrating essentially equivalent baseline floor performance across trials. Again we noticed no statistically significant difference between performance in robot session and human session ($p = 0.24$ for ASD and $p = 0.54$ for TD) although the ASD group was closer to having a statistical difference.

TABLE IV. PERFORMANCE STATISTICAL RESULTS

	Robot session		**Human session**	
Participant	**Mean**	**STD**	**Mean**	**STD**
ASD	39.62	35.23	21.86	17.37
TD	47.49	24.98	48.03	35.42

IV. Discussion and Conclusion

We have presented a novel autonomous closed-loop robotic system for imitation learning for ASD intervention. The system is capable of administering gestures to the children, assessing the imitated gestures, and providing feedback, all in real-time. We have performed a user study to evaluate the efficacy of the system with an ASD and a control TD group. The results show that the presented robotic system was more engaging than a human therapist to the ASD group, and they performed better with the robot. Although no statistical significance was observed in the results, we believe that with more participants, we may observe such a difference. However, more experiments are needed to assess the benefit of such robotic systems conclusively.

Movement in this research direction introduces the possibility of technological intervention tools that are not simple response systems, but systems that are capable of sophisticated adaptations. Systems capable of such adaptation may ultimately be used to promote meaningful change related to the complex and important social communication impairments of the disorder itself. We do not propose this technology as a replacement for existing necessary comprehensive behavioral intervention and care for young children with ASD. Rather, our platform represents a move toward realistic deployment of technology capable of accelerating and priming a child for learning in key areas of deficit across these very same intervention environments. With careful design, robot-led imitation intervention systems have great potential to draw children with ASD into interactions and effectively (and enjoyably) teach children new skills.

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