Teaching a robot dog new tricks: User interaction with trained versus pretrained robot dog

Olivia Tomassetti, Sawyer Paccione, Stephanie Bentley,

Mechanical Engineering
Tufts University
Medford MA, USA
December 16, 2021

Contents

1 Introduction

The goal of our project was to understand how training a robot may impact how the user feels towards the robot. Having users train their robots may increase user attachment towards the robot as well as user understanding of how the robot learns to accomplish tasks. In comparing user interaction with a pre-trained robot to an interaction during which the user trains the robot, we hoped to understand the advantages of users training their robotic systems, which may have potential impacts on the development and acceptance of commercial robots as they expand into homes and other social settings. Since there has been little research conducted on comparing pre-trained and trainable robots, we hope to use the results of our study to begin to understand the advantages of users training robots.

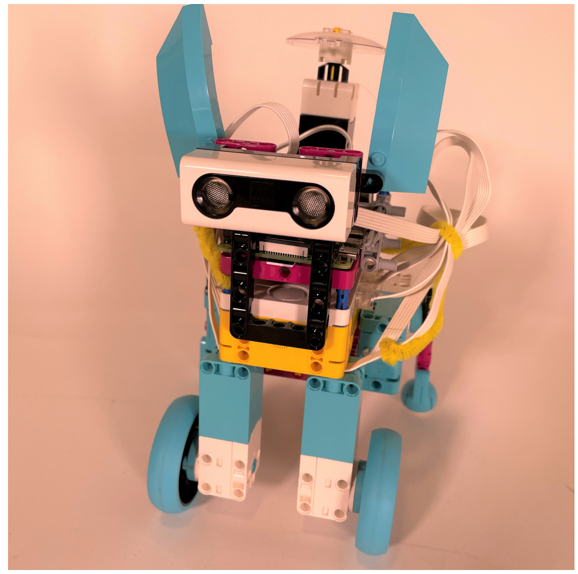

Figure 1: Spike Standing

To achieve our goal, we built two user-friendly dog robots using LEGO SPIKE Prime kits and Raspberry Pis. Incorporating a Raspberry Pi with the LEGO hardware added more capabilities to our robot. We then implemented two different programs - one for the pre-trained dog robot and the other for the trainable robot. We designed a training algorithm that utilizes Reinforcement Learning by taking data from the sensors to update the probability that a certain action will occur in response to a participant's voice command. When running this algorithm, the robot dogs were trained by participants to sit. The trained dog would respond to commands 'down', 'stand', 'come', or 'spin'. From here, a novel social science study was run.

Participants included undergraduate and graduate students at Tufts University with varied fields of study. The study was run as a within-participants study, with each participant being exposed to our two conditions in random order. In one of the conditions, a participant interacts with a pre-trained dog, and in the second condition, participants train the dog themselves and then interact with it. The order of these conditions was randomized to reduce biases. During the study, we focused on four main metrics: animacy, affinity, engagement, and predictability. The number of times the participants referenced a dog robot with a pronoun or name was used to measure animacy. We related the number of words spoken by the participants to the robot to measure engagement. We measured predictability by the number of 'surprise' words the participant said during the session. Additionally, we included a questionnaire that directly relates to the metrics we are measuring to see how training the dog robots affected the participants' views of the robot.

The effects on users who train robots is just beginning to be explored. Unlike many past studies, we are specifically looking at the effects of the users teaching the robot versus at how the robot learns. For our approach, we are building robotic dogs since humans are already accustomed to training real dogs; therefore, training a robot that looks like a dog is a natural progression. We expect participants to feel greater affinity and express deeper engagement towards the robots in the condition where they train the robot as well as attribute greater animacy for the robot as it would appear more dog-like. Finally, we expect predictability to increase when the participants have more direct involvement in the robot learning in the training condition as opposed to the pre-trained robots. Overall, we expect the users to feel more positively towards the robots they have trained and have a better understanding of how the robot learned.

2 Background

As technology continues to progress in our society, more and more people will come in contact with robotic systems every day. Therefore, it is important that we consider the societal reception of robots when engineering and designing these systems. For our research, we considered prior work that has been done in robotics relating to reinforcement learning, emotional reactions to robots, and building robots to invoke reactions.

Advanced robotic systems often rely on reinforcement learning methods to enable robots to adapt to expected tasks and behavior. Many algorithms and techniques exist to incorporate reinforcement learning into the motor skills that robots rely on, such as improved control algorithms [1]. Recent research has also focused on incorporating animal training techniques, such as shaping or classical conditioning into the algorithms that robots use to learn [2], [3]. Furthermore, prior work has experimented with using real-time human interaction to guide the learning and reward systems, developing robots towards the ideal of active learning from human interaction [4]. These learning interactions have also been expanded to virtual characters, improving the ability of robots to learn from their environments [5]. This study will utilize similar reinforcement learning algorithms to investigate human engagement with and perception of robot training. We chose to implement a simple reinforcement learning algorithm to best mimic classical conditioning as classical conditioning is typically how real dogs are trained.

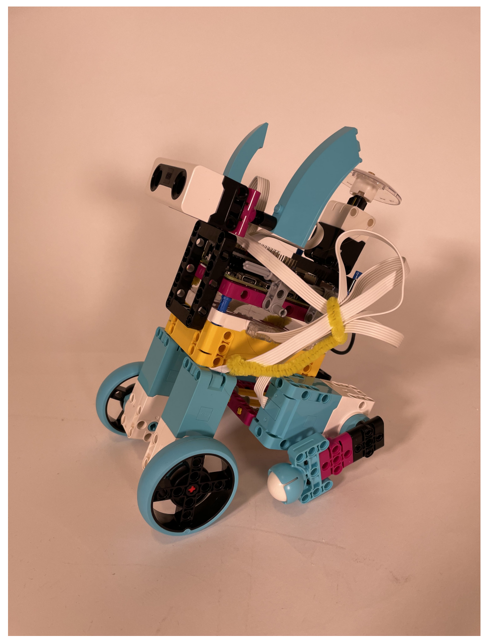

Figure 2: Spike Sitting

What makes a robot a dog? According to prior research, on top of its physical characteristics, a robot's intelligence, agility, and behaviors convey that it is a dog-inspired system, and not just another quadruped robot [6]. Cameras placed on the robot dog can be used to recognize hand motions for training and allow the robot to make eye contact. This increases the ability for participants to form a connection with the robot dog [7]. Additionally, the added physical characteristic of a tail on the robot dog not only makes the robot look more like its real-life counterpart but also allows the robot to express itself like it too. The inclusion of a tail used to convey motion resulted in participants being able to understand the robot's behavior more than without the tail [8]. When constructing the dog robot for our research, we attempted to incorporate the implications of these prior works, especially in terms of mimicking dog-like commands and behaviors for the training process to reinforce the parallel to a real dog. Although our dog was unable to use a camera to recognize hand motions, its ultrasonic sensor allowed it to stop when it was close to the human and its microphone allowed it to respond to user voice commands. Additionally, although it was not actuated, the battery wire acted as a tail to make the robot look more like its real-life counterpart.

Before designing our study, we also looked at research that previously highlighted the effects of users training robots. Much of the research that has been done focuses on how the robot is affected by these training interactions. When training a robot dog, most studies treat the training provided by humans as numeric rewards. Where this falls flat is when the trainers are inexperienced, or the learning algorithm isn't designed to understand the subtleties of the human trainers; instead, a proposed probabilistic model can often be more appropriate [9]. Yet, to utilize robots in a social role, and in turn conceivably increase positive user reception of these systems, researchers have begun to look at the effects on humans in interactions where human users are training or teaching robots. Prior research indicates that using expected reactions in human-robot interactions improves the efficiency of training, for example, more dog-like reactions improve training time for a dog robot [3]. These studies were valuable to determine the potential effects of training the robot and considerations for designing our interaction. Finally, a study by Hood, Lemaignan, and Dillenbourg found that learning through teaching, specifically, children teaching a robot to improve its handwriting skills can increase learning engagement in the participants, which may improve the effectiveness of learning activities overall [10]. This study is most relevant to our work as it provides insight into how teaching or training robots can impact the human rather than focusing on the robot. Our study builds off this work by extending the scope to consider more fully the relationship between participants' perception of the robot and training the robot themselves. Overall, not much has been previously researched about the effects on the human in using a pre-trained robotic system versus one that the human trains themselves.

Through our research, we plan to determine whether allowing a user to train a robotic system will increase the user's acceptance of and affinity towards the robot. To do this, we will build a robotic dog for our study since dogs are commonly trained by humans. The dog will sit, stand, and bark and be implemented with a reinforcement learning algorithm. Based on the previous work we reviewed, and specifically the work by Hood et al. [10], we predict that the participants will feel a stronger connection and understanding of the robot that they train themselves vs. the one that is pre-trained, resulting in an increase in the metrics for animacy, affinity, engagement, and predictability.

3 Methods

3.1 Participants

We had a total of 12 participants for the study - 6 females and 6 males between the ages of 19-39 years. All participants either somewhat or strongly agreed that they like robots. 8 of the 12 participants somewhat or strongly agreed that they have lots of experience with robots while 1 participant strongly disagreed and 1 participant did not agree nor disagree. Half of the participants either somewhat or strongly agreed that they want to pursue a career related to robots. The un-diverse robotics backgrounds of the participants are likely a source of error in our data. We conducted a within-participant study where each of these participants interacted with the robot while running the two different conditions to account for differences in personality or natural tendencies of each participant during the interaction.

3.2 Data Collection

During the study, a participant interacted with the dog robot under pre-trained and trainable conditions. Using two dog robots, two participants were able to complete the study at the same time in different rooms, which contained only the participant and researcher and were void of distractions to avoid confounds from the environment. For each session, the participant was either introduced to Spike, the trainable dog robot, or Prime, the pre-trained robot, first. This was randomized to reduce bias. When introduced to Prime, the participants were told that the robot would respond to the following commands: "down" to sit, "stand" to stand up, "come" to move forward until it reaches an obstacle, and "spin" to move in a circle. The participants were then given 3 minutes to play with Prime. When introduced to Spike, the participants were told that Spike was not trained. Their task was to train Spike to sit with the command "down". To do this, they were told to say the command after the robot beeped, and reward the robot by petting its back if it performed the task that was asked. The participants were then given 3 minutes to play with Spike. Between conditions, the robot's attire was changed from one colored bow to another colored bow to imply the participant was interacting with different robots so that they would be able to perceive the robots separately. The researcher brought the dog outside of the room to switch the bow in order to better convince the participants that there were two separate robots.

Both conditions involved the participants interacting with the robot for 3 minutes to minimize how different exposure time may affect participants feelings towards the robots between conditions. Since the robots cannot generate significant forces and have no dangerous components beyond the risk of a swallowing hazard, the safety of the participants was protected. A script was used to avoid variations in instructions between conditions and trials and any differences in response that those variations may cause. The full script that the researchers read from during the study can be found in section A of the Appendix, and the algorithms for implementing the conditions are described in Section 3.3. The privacy of participants was respected by storing videos and data of participants in a secure location and assigning each participant a unique number to refer to the data rather than personally identifying information. This study protocol was approved by the TA, Allison.

3.3 Algorithm

3.3.1 Pre-Trained Dog Robot

For the pre-trained dog algorithm, we wrote code that listened for the commands, "down", "stand", "come", or "spin" using the microphone and performed the action corresponding with the word. After our original study tests, we decided to use a Wizard-of-Oz method to complete the pre-trained dog section of the study. Although the original code we designed for the pre-trained dog was able to use voice commands for the dog robot to perform the desired actions, our microphones would not consistently pick up correct voice commands. The dog seemed to pick up the word "down" most often. Therefore, in order to understand user preference between the pre-trained and trainable robotic systems, and not about whether the pre-trained dog listened consistently, we decided to control its actions ourselves and have users train the trainable robot to sit using the command "down".

3.3.2 Trainable Dog Robot

Algorithm 1 Reinforcement Training Algorithm

```
Require: userSpeech, userInput, weights
Ensure: Dog is in the standing position
  while dogInTrainingState() do
      command ← speechRecognition(userSpeech)
      if command = down or stand or come or spin then
          action ← chooseAction(command, weights)      ▷ Probabilistically Chosen
          performAction(action)
          correctAction ← checkPraised(userInput)
          weights ← updateWeights(correctAction)
      end if
  end while
```

The trainable dog robot ran a simplified reinforcement learning algorithm that we designed. The dog could perform 4 actions "down", "stand", "come", or "spin" (although during the study we asked the participants to train the dog to sit using "down"). The robot could receive commands using a user's vocal input and a speech recognition library. If one of the commands is given to the dog, it will perform an action based on probabilistic weights. There are four sets of four weights, one set of weights for each possible command and four weights for each possible action. The weights start equal and are tied to each word. See Table 1 for a visual representation.

		Actions			
		Down	Stand	Come	Spin
Commands	Down	$p_{down,down}$	$p_{down,stand}$	$p_{down,come}$	$p_{down,spin}$
	Stand	$p_{stand,down}$	$p_{stand,stand}$	$p_{stand,come}$	$p_{stand,spin}$
	Come	$p_{come,down}$	$p_{come,stand}$	$p_{come,come}$	$p_{come,spin}$
	Spin	$p_{spin,down}$	$p_{spin,stand}$	$p_{spin,come}$	$p_{spin,spin}$

Table 1: Action Probability Matrix

After performing the chosen action the dog will await the user's feedback. Feedback was received by a force sensor on the dog robot's back, positive feedback was a 'pat' on the location of the force sensor and negative feedback was a lack of a 'pat'. Positive feedback would increase the weight of the action chosen for the user's command, decreasing all the others. Negative feedback would decrease the weight of the chosen action for the user's command, and increase all the others. For example, if the user said 'down', the robot would choose its action based on the probabilities in the row labeled 'down' (i.e. it chose action x with probability $p_{down,x}$). Let's say the dog chose the correct action 'Down'. When the user 'pats' the dog robot's back to provide positive feedback the probability of choosing down $p_{down,down}$ would be increased and the other probabilities ($p_{down,stand}$, $p_{down,come}$, $p_{down,spin}$) would be decreased. Conversely, if the dog robot chose the incorrect action 'Stand'. Then when the user did not give positive feedback, the probability of choosing stand $p_{down,stand}$ would be decreased and the other probabilities ($p_{down,down}$, $p_{down,come}$, $p_{down,spin}$) would be increased. Due to the setup of the algorithm, it was possible for the user to train the dog incorrectly.

3.4 Data Processing

Both audio and video data were collected during the participant interaction with each dog robot. A questionnaire was given to each participant after they completed both conditions. The questionnaire included Likert survey questions for each robot dog. Table 2 shows the behavior and survey measures we used for each metric. We included at least two measures for each metric. Additionally, we collected qualitative data from participants' self-reported responses to the questions "Which dog robot seemed more like a real dog?" and "Which dog robot did you enjoy playing with more?".

3.4.1 Video Processing

After the trials, we watched the videos of the participants whose sessions we ran. We annotated the videos specifically looking for the following during each of the 3 minute interactions they participated in: (1) The amount of pronouns, names, or nicknames the participant used to refer to the robot, (2) the amount of positive words or actions

Metric	Animacy	Affinity	Engagement	Predictability
Behavior Measures	How many pronouns, names, or nicknames participant used to refer to the robot during each session	How many positive and negative words or actions used towards robot during each session	Amount of words the participant says to the robot during the session that are not commands	How many surprise words the participant uses during the session
Survey Measures	My interaction with the robot was similar to an interaction with a real dog (Likert Scale)	I enjoyed interacting with the robot (Likert Scale) I would like to interact with this robot again (Likert Scale)	I would like to interact with this robot again (Likert Scale) Did the length of your interaction with the robot feel too long, too short, or just right?	The robot performed the actions that I expected (Likert Scale)

Table 2: Metrics and Measures

directed to the robot, (3) the amount of negative words or actions directed to the robot, (4) the number of times the participant touched the robot (not including when the participant touched the force sensor), (5) the amount of words that the participant used towards the dog (not including commands given), and (6) the amount of surprise words the participants used during the session. Some example phrases we looked for when counting each of these measures are shown in 3. Although we tried to make these measures specific, we realize that the subjectivity and variability of the annotations likely affected the analysis of our results.

Measure	1	2	3	4	5	6
Examples	"buddy", "he", "Prime"	"good job", "its doing so well", "so cute"	"poor guy", *fake hitting action, "bad dog"	Helping the dog up, moving the dog to face participant	N/A	"oh I see", "that was quick", "impressive"

Table 3: Example phrases found while annotating videos. Measures 1-6 listed in paragraph above.

3.4.2 Questionnaire Data Processing

To process the questionnaire data, we subtracted the responses to the Likert scale questions for Prime from the responses for Spike and generated mean and standard deviation statistics for these differences. For the open-ended questionnaire answers, we conducted a thematic review to pull out main themes in the participants' responses.

3.4.3 Statistics for Quantitative Data

To compare the data within participants, we took the data from the video annotations, as well as from the quantitative survey questions, and found the difference between the trials with Spike (the robot trained in trial) and Prime (the pre-trained robot). From these differences, we calculated the mean as a measure of center and the standard deviation as a measure of spread. Additionally, we conducted a two-tailed paired t-test with the data from Spike and the data from Prime for each measure to determine whether the conditions were significantly different, with a significance threshold value of $p = 0.05$.

4 Results

The following graphs and tables show the results from our study. During the implementation of the robot, some limitations in the hardware skewed the data presented. For example, once the dog robot sat, it sometimes had a difficult time standing back up. Additionally, the microphone did not always pick up the command that the participants had said. Due to the design of our study, it was important that the dog robot was able to hear the participant correctly every time the participants said a command. Additionally, it was important that the robot motors and sensors worked consistently. Yet, due to the hardware limitations, neither of these were true and likely skewed our data.

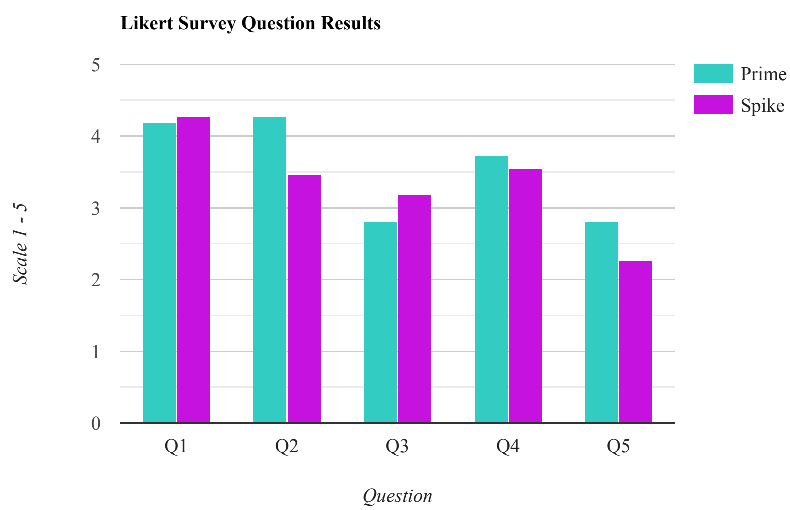

Figure 3: Likert Survey Questions

Figure 3 shows that, on average, participants enjoyed interacting with Spike, the trainable dog robot, only slightly more than they enjoyed interacting with Prime, the pre-trained dog robot. However, as shown in Figure 4, when asked to choose between the two robots almost all participants said that they liked Spike more. One participant

Q1	On a scale of 1-5, indicate whether you agree (5) or disagree (1) with the following statements: - I enjoyed interacting with the robot
Q2	On a scale of 1-5, indicate whether you agree (5) or disagree (1) with the following statements: - The robot performed the actions that I expected
Q3	On a scale of 1-5, indicate whether you agree (5) or disagree (1) with the following statements: - My interaction with the robot was similar to an interaction with a real dog
Q4	On a scale of 1-5, indicate whether you agree (5) or disagree (1) with the following statements: - I would like to interact with this robot again
Q5	Did the length of your interaction with the dog, feel too long (3) or too short (1)

Table 4: List of Likert Questions

Metric	Measure	Source	Mean difference	Difference Standard Deviation	Paired t-test result	Effect on Metric
Animacy	Pronouns, names, and nicknames	Video	-0.917	3.204	0.343	Decrease
	Similar to real dog	Survey	0.364	1.120	0.307	Increase
	More like real dog (self-reported)	Survey	1.545	0.522	N/A	Increase
Affinity	Positive Words	Video	1.083	1.975	0.084	Increase
	Negative words	Video	0.083	1.443	0.845	Decrease
	Touches	Video	-0.833	1.749	0.127	Decrease
	Enjoyed interacting	Survey	0.091	0.539	0.588	Increase
	Like to interact again	Survey	-0.818	1.722	0.146	Decrease
	Enjoy playing with more (self-reported)	Survey	2.000	0.000	N/A	Increase
Engagement	Number of non-command words	Video	-4.000	13.618	0.331	Decrease
	Like to interact again	Survey	-0.182	0.751	0.441	Decrease
	Length of interaction	Survey	-0.545	0.934	0.082	Increase
Predictability	Surprise Words	Video	0.500	1.931	0.389	Decrease
	Robot performed expected actions	Survey	-0.818	1.722	0.146	Decrease

Table 5: Quantitative Statistics by Metric

said that they liked Prime more; however, that participant said "it felt gratifying to train Prime," seemingly suggesting that they could have mixed up the names of the dog robots. Additionally, Figure 3 shows that, on average, participants agreed that their interaction with the robot felt more similar to an interaction with a real dog when playing with Spike than when playing with Prime. Participants agreed more strongly that Prime performed the actions that they expected versus Spike and, on average, agreed slightly more that they would like to interact with Prime again. Additionally, participants wanted more time to interact with Spike compared with Prime.

Table 5 summarizes the statistics generated from the survey results using the difference between the Spike (trainable) and Prime (pre-trained) conditions to compare within participants, including the mean as a measure of center, standard deviation as a measure of spread, and a paired t-test with all of the data sets in order to determine whether the difference between conditions was significant, using a threshold significant value of 0.05. In Table 5, the survey measures and the video annotations did not always agree in terms of our metrics of animacy, affinity, engagement, and predictability. For every measure, the paired t-test result value is greater than the significance threshold of 0.05, indicating that the conditions are significantly different for each measure. However, the standard deviations of the differences between conditions are frequently double or more of the mean of the differences.

In terms of animacy, the results of the survey measures both reveal a slight increase, corresponding to an increase in the animacy of Spike (trainable) compared to Prime (pre-trained), however the video annotation measure of the number of named references to the robot reveal a decrease corresponding to a decrease in animacy of Spike compared to Prime. In terms of affinity, the positive means indicate an increase of positive words and an increase in "enjoyment interacting with the robot" indicating an increase in affinity towards Spike compared to Prime, while the increase in negative words, the decrease in number of touches, and the decrease in "like to interact again" indicate a decrease in affinity towards Spike compared to Prime, presenting conflicting results. Similarly, for engagement, the mean decrease in number of non-command words and responses to the "like to interact again" question suggest a decrease in engagement with Spike compared with Prime, while responses to the "length of interaction" ques-

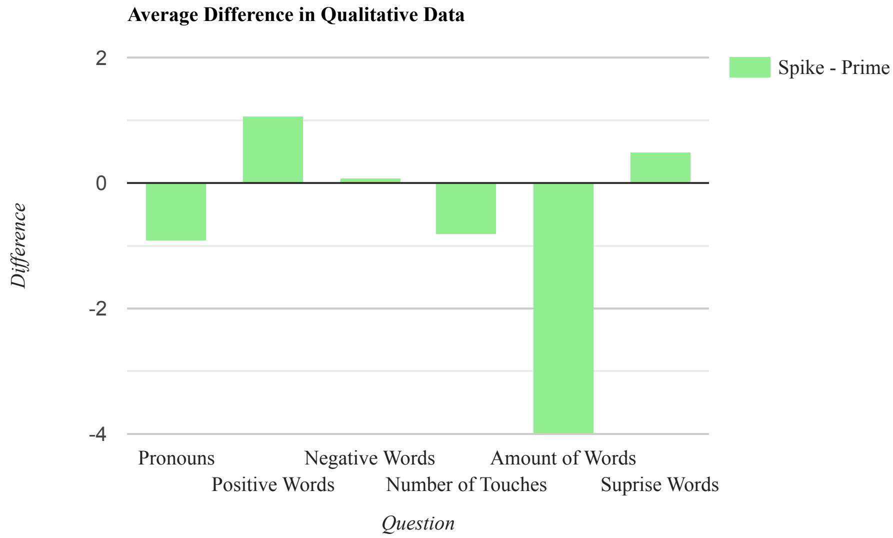

Figure 4: Average Difference of Annotated Data

tion indicate a desire to engage further with Spike in comparison to Prime. Finally, for predictability, both measures indicate a decrease in the predictability of Spike in comparison with Prime.

Questions	Responses for Prime	Responses for Spike
"Which dog robot seemed more like a real dog?"	Behavior more expected	→ Prime malfunctions → Unpredictable and uncooperative → More interactive
"Which dog robot did you enjoy playing with more?"	N/A	→ Felt rewarding and successful → More interaction with dog → Unexpected and unpredictable behavior exciting

Table 6: Thematic Analysis of Qualitative Survey Responses

The qualitative results to the questions asking for explanations of "Which dog robot seemed more like a real dog?" and "Which dog robot did you enjoy playing with more?" were collected from the survey and organized into themes using thematic analysis. The responses to "Which dog robot seemed more like a real dog?" seemed to depend on participants' expectations for a normal dog, with some saying the predictable behavior of Prime was more dog-like while others said the unpredictability of Spike was more realistic. Additionally, other themes related to labeling Spike as more realistic include more technical malfunctions with Prime and the greater level of interaction with Spike. Almost all participants chose Spike for "Which dog robot did you enjoy playing with more?", and the themes reveal that Spike was less predictable, but training Spike increased engagement and affinity towards Spike compared to Prime.

5 Discussion

Through this study, we gained conflicting conclusions. The survey measures and the video annotations did not always agree in terms of our metrics of animacy, affinity, engagement, and predictability. From the survey data, we can conclude that the trainable algorithm resulted in higher opinions of the dog robot's animacy and participant affinity towards the robot, which is in line with our original hypothesis. Although the differences between the ratings for the dogs are statistically significant, the trends for both dog robots between the different questions are similar. The video annotations suggest that participants treated Prime as more animate than Spike since users referenced Prime, using pronouns, nicknames, or names towards the robot, more often than Spike. Additionally, the video annotations show more negative words towards Spike and less touches, both indicating a decreased affinity towards the Spike robot. However, due to hardware limitations, it often was the case that Spike and Prime would not always stand back up after it sat down and participants would help the dogs by picking them up. This did not always occur and did not evenly occur between the two conditions. Therefore, the amount of times the user touched the robot was not necessarily directly correlated to the user's affinity towards the robot.

We originally predicted that Spike would be more predictable because the participants themselves train the dog so, in turn, understand what the dog should do and how the robot does it. However, unlike our hypothesis, the participants agreed that Prime, the pre-trained dog robot, performed the actions that they expected over Spike. Looking at these limitations, we realized that Spike might be more predictable after the dog robot has been trained, but, since the interaction was only 3 minutes long, the interaction consisted of training the robot, not using the robot once it is trained by the user. This is a study error and likely accounts for why we obtained the opposite results than what we expected in terms of our predictability metric. In terms of our measures of engagement, the survey results show mixed results. Although participants agree more that they'd like to interact with Prime again, the participants also agreed that they would have liked more time with Spike. Some of the variability may have resulted from the order of conditions in the study, which was not changed to reflect the order the participants performed the conditions in. The video annotation data shows that participant engagement with the robot was greater for Spike than for Prime, showing a decrease in engagement from Spike to Prime.

Due to the inconsistent nature of the hardware of our system, much of our data is not necessarily an accurate representation of what we attempted to determine. Although some of our data agrees with our hypothesis, different measures for each metric contradict each other. Therefore, it seems that more testing with longer condition settings would need to be done to make more definite determinations about which algorithm, the pre-trained or the trainable, best allows humans to connect with and understand the robot. Given longer trials and more consistent hardware, we may find results that better align to our hypothesis that trainable robots increase user connection and understanding of the system.

Bibliography

[1] E. Theodorou, J. Buchli, and S. Schaal, "Reinforcement learning of motor skills in high dimensions: A path integral approach," in *2010 IEEE International Conference on Robotics and Automation*, ISSN: 1050-4729, May 2010, pp. 2397–2403. DOI: 10.1109/ROBOT.2010.5509336.

[2] Y. Maeda and S. Hanaka, "Differential reinforcement-type shaping Q-Learning method based on animal training for autonomous mobile robot," in *2008 IEEE International Conference on Fuzzy Systems (IEEE World Congress on Computational Intelligence)*, ISSN: 1098-7584, Jun. 2008, pp. 2066–2071. DOI: 10.1109/FUZZY.2008.4630654.

[3] Y. Seiji and Y. Tomohiro, "Training AIBO like a dog - preliminary results," in *RO-MAN 2004. 13th IEEE International Workshop on Robot and Human Interactive Communication (IEEE Catalog No.04TH8759)*, Sep. 2004, pp. 431–436. DOI: 10.1109/ROMAN.2004.1374799.

[4] M. Ullerstam and M. Mizukawa, "Teaching robots behavior patterns by using reinforcement learning: How to raise pet robots with a remote control," in *SICE 2004 Annual Conference*, vol. 1, Aug. 2004, 143–146 vol. 1.

[5] C. Gatzoulis, A. Sourgoutsidis, V. Hurmusiadis, and W. Tang, "Adaptive Social Skills for Robots Interacting with Virtual Characters in Real Worlds," in *ROMAN 2006 - The 15th IEEE International Symposium on Robot and Human Interactive Communication*, ISSN: 1944-9437, Sep. 2006, pp. 8–13. DOI: 10.1109/ROMAN.2006.314387.

[6] H. Kitano, M. Fujita, S. Zrehen, and K. Kageyama, "Sony legged robot for RoboCup challenge," in *Proceedings. 1998 IEEE International Conference on Robotics and Automation (Cat. No.98CH36146)*, ISSN: 1050-4729, vol. 3, May 1998, 2605–2612 vol.3. DOI: 10.1109/ROBOT.1998.680735.

[7] R. Singh, B. Seth, and U. Desai, "A Real-Time Framework for Vision based Human Robot Interaction," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, ISSN: 2153-0866, Oct. 2006, pp. 5831–5836. DOI: 10.1109/IROS.2006.282397.

[8] A. Singh and J. E. Young, "A dog tail for communicating robotic states," in *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, ISSN: 2167-2148, Mar. 2013, pp. 417–417. DOI: 10.1109/HRI.2013.6483625.

[9] R. Loftin, B. Peng, J. MacGlashan, *et al.*, "Learning something from nothing: Leveraging implicit human feedback strategies," in *The 23rd IEEE International Symposium on Robot and Human Interactive Communication*, ISSN: 1944-9437, Aug. 2014, pp. 607–612. DOI: 10.1109/ROMAN.2014.6926319.

[10] D. Hood, S. Lemaignan, and P. Dillenbourg, "When Children Teach a Robot to Write: An Autonomous Teachable Humanoid Which Uses Simulated Handwriting," in *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, ser. HRI '15, New York, NY, USA: Association for Computing Machinery, Mar. 2015, pp. 83–90, ISBN: 978-1-4503-2883-8. DOI: 10.1145/2696454.2696479. [Online]. Available: https://doi.org/10.1145/2696454.2696479 (visited on 10/05/2021).

Appendices

A Participant Instructions

Participant Instructions - Spike Start

[Put on green bow]

[Greet person]

Thank you for agreeing to participate. This study is purely for learning purposes, to better understand how humans and robots interact. Would it be okay if we recorded audio and video during your session?

If yes: Great! Thank you! **[Turn on video camera]**
If no: No problem! [Researcher writes down observations]

At any time during the session, please let me know if you wish to stop the study.

During this session you will interact with two different dog robots. The first robot's name is Spike. Spike has not yet been trained. Your task is to train Spike to sit using the command "down". In order to do this, you will be saying the command "down" aloud after Spike's initial beep and rewardirng it if it completes the correct action. Since Spike is untrained, Spike may perform another action, including standing up, spinning in a circle, or moving forward until it reaches an obstacle (you, a wall, etc.). If Spike does not perform any action after your command, try saying that command again. If Spike performs the action you gave it, reward Spike by petting its back aka pressing on this force sensor [researcher points to force sensor]. If Spike does not respond correctly, wait a few seconds. In either case Spike will beep to indicate Spike is ready for the next command.

To reiterate, after saying the word "down", you want Spike to sit.

Try to say the words loudly and clearly. If Spike does not perform any action, try a command again. Spike cannot always hear its human.

The instructions to train Spike are also listed here.

1. Wait for Spike to beep
2. Say your command
3. After Spike performs an action, press the button on its back if that action was correct. Otherwise wait for the beep to repeat
4. Repeat

Please let me know if you want me to repeat these instructions or if you have any questions.

Please give me a moment to set up.

[run spike.py and set timer for 3 minutes]

[3 minutes]

Figure 5: Participant Instructions - Spike Start Page 1

[1]

[1] The instructions for the condition where Spike was shown first were simply the reverse of the Figures 5 and 6

Great! Thank you! Please give me a minute to go get the next dog robot. [Go outside and switch bows to blue]

You will now have some time to play with another dog robot named Prime. Prime looks similar to Spike; however, Prime is already trained. Prime has been trained with the following commands: down, stand, come, spin. When you say these words to Prime, it should perform the action.

After saying the word “down”, Prime will sit.

After saying the word “stand”, Prime will stand.

After saying the word “come”, Prime will drive forward until it sees an obstacle (you, a wall, etc) then stop.

After saying the word “spin”, Prime will spin in a circle.

Prime will beep to indicate that it is ready to listen. Try to say the words loudly and clearly. If Prime does not perform the command you asked, try that command again. Prime cannot always hear its human.

Please let me know if you want me to repeat these instructions or if you have any questions.

Please give me a moment to set up.

[Researcher runs prime.py, sets timer for 3 minutes]

I will now give you three minutes to play with Prime. Go ahead! [Start timer]

[3 minutes]

Thank you!

The last task is to complete this survey. I will ask you to complete the survey on my computer.

[Enter participant number in survey]

[give participant your computer to complete survey]

Thank you for participating. We greatly appreciate it!

Figure 6: Participant Instructions - Spike Start Page 2