Coherent Personality Elicits Better Human Teaching

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***Abstract*—We conducted an experiment to assess whether a robot's coherent expression of emotion affects the teaching it receives. Participants were asked to demonstrate dances to a robot for her to imitate; the accuracy and frequency of the participants' demonstrations was measured. Every time the robot danced, her performance was scored and then she reacted to that score with either a relevant emotional response (in the experimental group) or an emotional response chosen at random (in the control group). Although in both groups the robot learned at the same pace and received the same scores, people taught significantly more frequently and significantly more accurately to the emotionally-coherent robot.**

I. Introduction

Although and models of personality and emotion have been developed and studied by psychologists, cognitive scientists, and computer scientists alike [9], we don't yet know the generalizable benefits of applying emotion modeling to human-computer and human-robot interaction. What does emotion modeling contribute to such interactions?

The most significant benefit of robots that exhibit emotion, we believe, is the user engagement that such robots can foster. Robots that produce convincing and consistent emotions can engender a deeper sense of investment from people who interact with them. Creating such robots may yield a better collaborative environment between people and robots. Here we examine the effects of a robot's display of emotion on people's behavior in a specific type of collaboration: how much people are invested in teaching a robot.

Teaching is of specific interest because as robots become more involved with our daily lives, their value to us will grow with their ability to adapt and learn from users. The more engaged and invested people are when they teach robots, the more and better teaching they want to produce. The better the teaching the robot gets, the easier it can learn. We assess whether an emotion model better engages people in this task.

Our results suggest that robots that express believable and coherent emotion do receive better teaching.

II. Related Work

Rather than people having to program robots, a job that requires specialized knowledge and often proves quite difficult, it remains a grand challenge of social robotics to create robots that learn from people's natural teaching styles and modes [1]. To build effective learning robots, human-robot interaction designers need to know what input to expect. Some researchers approach this by deconstructing natural human teaching into three constituent processes: demonstration, feedback, and repetition [14]. We and others have worked on documenting what sorts of *feedback* robot designers can expect to receive from human teachers [12]. Now our aim is to encourage the production of more and better demonstrations when people teach robots.

It's no news that crafting emotionally believable characters, agents, and robots produces user/consumer investment and engagement [3] [18]. In fact, such feats are companies like Disney's bread and butter [11]. But the usefulness of creating emotionally believable characters, beyond their entertainment value, is rarely studied. Here we propose one such use of this craft: the elicitation of more and better human-to-robot teaching.

Since the effect of emotion on cognition is thought to be very significant [15], many researchers have constructed models of emotion for virtual agents [10] and robots [5] to contribute to the agent's or robot's decision-making process. Whereas this work sees emotion modeling as a stepping stone toward more human-like and/or more sophisticated behavior, our approach uses emotion to create a character that engages people and here we assess the benefits of that engagement.

In other branches of research, users' perception of a robot's emotions [3] and a robot's perception of users' emotions [6] have been studied. This research highlights the role of users' emotions, either in how people come to feel about a robot based on its features (e.g. embodiment) or how a robot can identify and respond to its users' emotions. Unlike this research, our work doesn't categorize or interpret the emotions experienced by the user; rather, we measure the effects of a robot's emotions on the user's behavior.

There are several studies and proposed methodologies designed to assess the effectiveness of various emotion models [7] [8], but these studies concern either the accuracy of reproducing human emotion or the likability of particular models of emotion. Instead, we assess the effect of an emotion model on human behavior in human-robot interaction.

What we offer, in contrast to all the work discussed above, is a behavioral measure of engagement in the act of teaching a robot that exhibits believable emotion.

III. Personality & Emotion Modeling

A. Background

Models of emotion predict and simulate the process by which people map their experiences to emotional states. We need such a mapping to pick which emotions are appropriate for our robot in various contexts in order to create an emotionally coherent and believable character.

The dominant psychological theory describing this process is called appraisal theory; it focuses on the role of an agent's assessment of his present experience relative to his goals, desires, and beliefs [17]. Appraisal theories propose a number of variables, called appraisal dimensions, that define the differences between emotional states. For example, an event's desirability, causality, and likelihood are often relevant to the emotions that the event elicits. An appraisal model might predict that a person considering an event that is desirable, caused by himself, and very likely to happen will feel a mixture of hope and pride.

The most influential appraisal theory in computation is the OCC model, published in 1988 [9] [16]. This model provides a hierarchy of appraisal dimensions by which it distinguishes 22 types of emotion. At the top of the hierarchy, emotional triggers are sorted into either: "consequences of events" (e.g. leading to satisfaction, or pity, or disappointment),"actions of agents" (e.g. leading to pride or admiration), or "aspects of objects" (e.g. leading to love or hate). At each further level in the hierarchy, the appraisal dimensions are specific to the branch they belong to: under "consequences of events", the dimension the model considers next is whether the consequences of that event are for itself or other agents, and under "other agents" the next dimension is whether that event is desirable, which concludes in a happy-for or resentment emotion, or undesirable, which concludes in a gloating or pity emotion.

Many researchers have implemented variants of the OCC model for virtual agents and robots. The biggest distinction between these implementations is in their choice of appraisal dimensions, whether adding new dimensions or selecting a subset of the OCC dimensions. Some variants drastically restructure the hierarchy that produced the original 22 emotion types [4], while others preserve the structure but pare away what they see as redundant or unnecessary emotion types [2]. Since the publication of the OCC model, there have been many proposed computational modifications and revisions to their original appraisal dimensions, but none has emerged as a consensus choice. For our model, we selected the appraisal dimensions we considered most relevant to the dancing task in our experiment.

More recent models of emotion have considered other aspects of the process of appraisal beyond the dimensions on which it operates [9]. For instance, the EMA model [13] accounts for moods, coping mechanisms, and multiple levels of appraisal. Our model incorporates some coping mechanisms in its library of emotional responses, but we chose not to use most of these more complex aspects of emotion modeling in favor of keeping our model easy to understand.

B. Our Model

Our model borrows two appraisal dimensions as they're specified in the EMA model [13] and takes some inspiration from its coping mechanisms, but does not implement the vast majority of its features. Since we aim to measure the effect of consistent emotional responses against ones that aren't, we created an emotion model that could be understood with relatively few observations. Our aim was to make its consistency quickly apparent.

In our model, we accounted for two emotion appraisal dimensions:

- **Desirability**, the agent's perception of the utility of an event. In our experiment, this referred the robot's perception of the scores she earned for each dance. Above 75% was considered desirable, and below 30%, undesirable.
- **Expectedness**, the extent to which the agent predicted an event. We always deemed the first score for each dance unexpected. After that, only when her score changed by $10\%+$ from one trial to the next was it was unexpected. Otherwise the robot treated the score as expected.

We chose these two dimensions because of their relevance to the dancing task we chose for the experiment. The scoring provided us an opportunity for frequent emotion-triggering events, and these appraisal dimensions are the most salient and easily-communicated emotional features of a sequence of scores.

These two dimensions were treated as binary values: either wholly true or wholly false. The possible combinations provided us with four kinds of emotion, to each of which we fit emotional descriptions as follow in Table I.

TABLE I
Types Of Emotion

	Expected	**Unexpected**
Desirable	satisfaction, pride	happy-surprise, relief
Undesirable	shame, frustration	disappointment, worry

Then these descriptions lead to specific emotional responses that fit one of these types. For a sample of the emotional responses that the robot said, see Table II.

The emotion model that we specify here was created to test the impact of a simple but consistent model of emotion on human-robot teaching. Below we describe the experiment that we conducted using this model.

IV. Experiment

In our experiment, participants were asked to teach our robot, who we called Kate, a set of short predefined dances. Participants were to demonstrate the dance moves for Kate to watch and imitate. After each dance, Kate received a score to which she responded with either an emotion consistent with our emotion model described above (for participants in the experimental group) or one chosen at random from all the available responses (in the control group). The robot's dancing

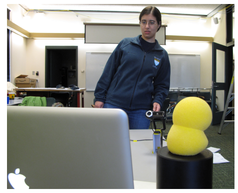


Fig. 1. A participant does a lean.

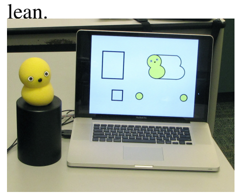


Fig. 2. Keepon and the dance instructions.

(a) Viewed from above, as a participant dances.

Fig. 3. The experimental set-up. Participants were asked to demonstrate the dances as instructed on the screen behind Kate (the robot), for her to watch and imitate.

and scores were consistent across conditions and participants, independent of the participants' demonstrations.

A. Robot

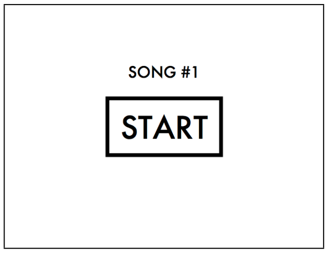
The robot we used, Keepon, is a small creature-like device with four degrees of freedom. (See Figure 2.) The robot can lean left and right, rotate 180 degrees in either direction, tilt forward and back, and bounce up and down. Keepon's skin is made of yellow silicone rubber that deforms as it moves. Keepon is snowman-shaped and rests on a black cylinder.

We referred to the robot as Kate throughout the experiment because the prerecorded audio files of Keepon's emotional responses and other vocalizations were made with a female voice.

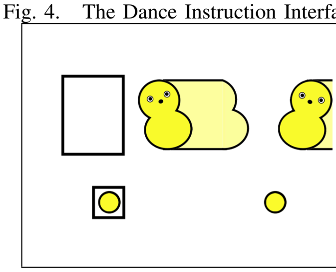
B. Experimental Setup

We asked participants to teach the robot five predefined dances, each set to a different half-minute pop song clipping (see Table III for the play list). The dance instructions were displayed on a screen behind the robot. (See Figure 2.) We illustrated the dances with an interface similar to those found in popular rhythm games like *Dance Dance Revolution* and *Guitar Hero*. Figures representing dance moves traveled across the screen from right to left until they reached a target box.

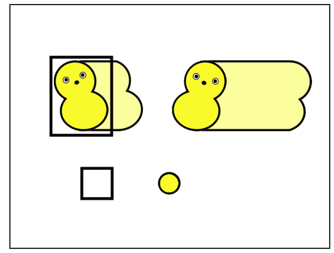
Fig. 4. The Dance Instruction Interface



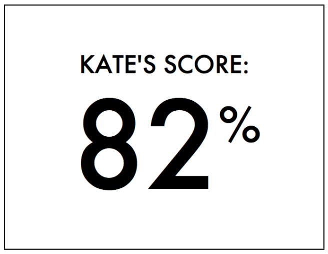
(a) The robot waits for the participant to press “START”. Meanwhile, she hums to herself and looks around the room.



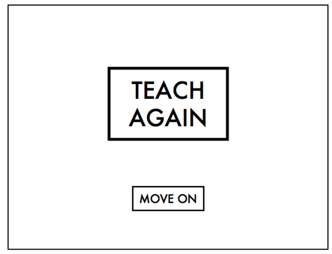
(b) The dance instructions scroll from right to left. The figures at the top represent leans, tiling your body left or right. The circles are bounces: scrunching your body down and back up.



(c) The dance moves are active when the figures reach their targets on the left.



(d) The robot gets a score for each dance, turns around to look at it, and responds emotionally.



(e) After every dance, the participant chooses whether to demonstrate that dance again or move on to the next one.

Fig. 5. These are the screens participants saw on the computer behind the robot.

See Figures 5b and 5c for illustrations of the dance instruction screen. Participants stood on a Nintendo Wii Balance Board (a wide and low-to-the-ground pressure-sensitive platform) in front of the robot. See Figure III-B for illustration of the environment.

C. Instructions

Participants were told that Kate would learn to dance by watching them demonstrate each dance. They could repeat each dance as many times as they wanted, but once they chose to move on from one dance to the next dance they could not go back. Participants were instructed to move on from one dance to the next when they felt Kate had done well enough. If participants asked the experimenter what score they should aim for, the experimenter told them to continue until they were satisfied with Kate’s performance. They were also told that Kate improves with every subsequent demonstration of each dance.

The experimenter did not mention the emotional aspect of the robot’s behavior. The experimenter also did not reveal that, internally, the participants’ dancing was being scored.

D. Dances

Each dance was a series of leans, left or right, and a concurrent series of bounces. To perform a lean, the participant was to shift his weight to one side of his body. Leans had varying lengths, indicated by a trailing shadow of the robot image on the screen (Figure 5c). A bounce was performed by bending one’s knees and then quickly standing upright again. Bounces could be executed during leans or separately.

On average, there were 13 seconds of leaning and 16 bounces required per 30-second dance. The dances ranged in complexity from 8 to 30 bounces and 8 to 20 seconds of cumulative leaning per dance.

A list of the dance songs we used is provided in Table III.

TABLE III
DANCE SONGS

Dance	Artist	Title	Cut
1	Willy Wonka	Oompa Loompa	$0:20-0:51$
2	Daft Punk	Robot Rock	$0:34-1:02$
3	Michael Jackson	Billy Jean	$0:26-0:58$
4	Basement Jaxx	Do Your Thing	$0:32-0:59$
5	Lady GaGa	Just Dance	$0:46-1:22$

E. Interaction

For each dance, participants demonstrated it as instructed on screen, observed Kate’s score and her response (figure 5d), and then decided whether to teach that dance again or move on to the next dance. Every time Kate finished a dance, she turned around to learn her score, she played an audio file of an emotional reaction to the score, such as “I really wish I had done better” or “Hey, cool, I did well.” Kate then turned

TABLE II
SAMPLE OF THE ROBOT'S EMOTIONAL RESPONSES

Score	Coherent Emotional Response	Randomized Emotional Response
20	"Oh no, ohh no."	"Whoa, look at that, that is an awesome score."
22	"Ugh, man, this is hopeless."	"Augh, that was bad, that was really bad."
82	"Ooh, check *that* out, we did great!"	"Oh no, that was terrible!"
89	"Now, how great is that."	"Oh yeah, that's right, un-huh."
91	"Cool, cool, we did well."	"Ugh, I'm so mad!"
94	"Ohhhhhh, yeah."	"Ooh, we're doing really well."
95	"Oh yeah, oh yeah, oh yeah."	"Hey, that score's pretty darn good."
97	"Yeah, well, I'm really good at this."	"Now, how great is that."
99	"Cool, cool, we did well."	"Ugh, oh no, I'm so sorry!"

back to face the participant and asked to play again. After the robot finished speaking, participants saw two buttons, one marked "Move On" and a larger one marked "Teach Again." See Figure 5e.

F. Scores

The robot's scores were percentages between zero and one hundred.

The sequence of scores the robot received for the demonstrations of each dance was fixed in advance and did not change across conditions or participants. With each repetition of any dance, the score always increased.

Each dance had a separate sequence of scores, but all of the sequences began with several low scores (all below 30%), followed by a large jump to a series of higher scores (all above 75%). The jump occurred on the third demonstration for each of the first three dances, on the fourth demonstration of the fourth dance, and on the fifth demonstration of the fifth dance. In each case the jump was at least 45 percentage points, and no other pair of adjacent scores was more than 5 points apart.

We set the scores up with these jumps to provide participants a convenient stopping point. That enables us to measure engagement more directly: was the participant patient enough to reach the jump? If so, how long did the participant demonstrate the dance after the jump?

The robot's performance during each demonstration of a dance was based on its score for that repetition. The correct moves for the dance were altered or deleted probabilistically, where the fixed score for that round determined the likelihood of an alteration or deletion. Nothing the participant did altered the robot's performance. In fact, across participants, the robot performed the same exact way on any given repetition of a dance.

G. Emotion

The robot's emotional responses to her scores were the only difference between the two groups. All other aspects of the interaction were the same between groups.

After each dance, the robot voiced an emotional response to her score. These responses were prerecorded audio clips, each of a few spoken English words in a female voice. We recorded eighty such clips, each fitting into one of the four emotion groups specified by our model of emotion. (See Table I above for descriptions of each group.)

For participants in the experimental group, when the robot got a score she used the following heuristic to decide if each score was expected or unexpected and desirable or undesirable:

- **Desirability** – 75% or above: desirable; 30% or below: undesirable. No scores were between these ranges.
- **Expectedness** – first repetition of each dance or score change $> 10\%$: unexpected, otherwise: expected.

Based on that decision, she played one of the twenty emotion audio clips fitting that specification. The particular clip among these 20 was chosen at random.

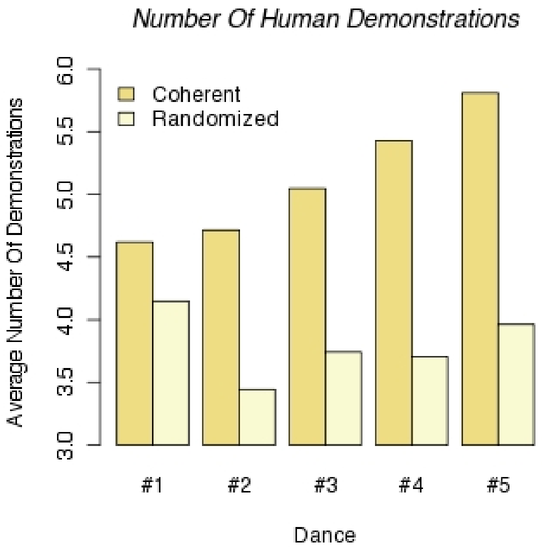
In the control group, however, the robot randomly selected one of the four types of emotion our model recognizes for each response. Again, the specific audio clip within the type was chosen randomly from the 20 possibilities in each category. See Table II for a sample set of responses for both groups.

We chose to randomize emotional response as a control because that strategy let us narrow down our independent variables; we can say with confidence that any difference between the groups is not because of distinctions between voices or speech content. The experimental group and control group experienced the same set of voice recordings, but in different order.

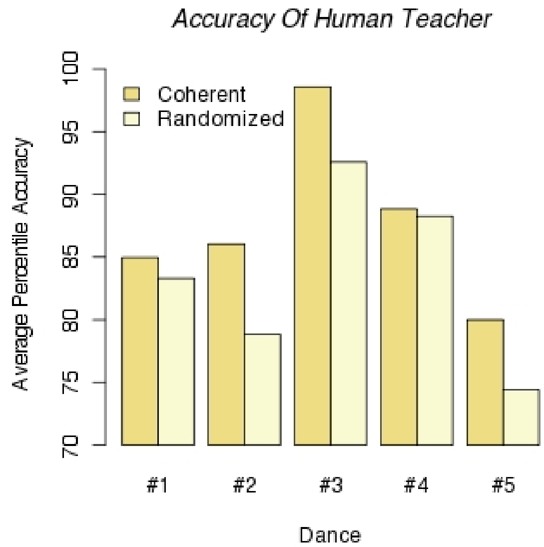
H. Data Collection

We measured the number of times participants chose to repeat each dance.

Participants stood on a Nintendo Wii Balance Board to demonstrate the dances, which allowed us to use the balance board's pressure sensors to collect information on when the participants performed the dance moves. We calculated two scores for each repetition of a dance. The first was the percentage of bounces that the participant performed at the time indicated by the dance on the screen, with a margin of error. The second was the percentage of time they leaned in the correct direction when a lean was indicated and did not lean when no lean was indicated. Our final measure of dance accuracy for that repetition was the average of the two scores. These scores were never shown on the screen and we did not tell participants that their dancing was being rated, though



(a) The average number of times participants chose to demonstrate each dance.



(b) The average percentage of the time that the participants demonstrated the correct dance move for each dance.

Fig. 6. Participants demonstrated the dances, on average, more often and more accurately in the coherent emotional responses group.

the screen did give instantaneous feedback on whether they were doing the right move. Any active figure would become translucent when the corresponding dance move was not being performed.

We also administered a survey after participants finished all five dances. We asked them to rate and describe the robot's learning and reactions, and to explain how they decided to move on from one dance to the next.

I. Participants

We recruited 48 participants, 18 years of age and above, from the Yale University and New Haven communities. Twenty-one subjects saw the coherent-model condition and 27 saw the randomized condition. Our exclusion criteria were lack of English fluency or extensive prior experience with robots or artificial intelligence (i.e. computer science graduate students, students having taken or currently taking a robotics or artificial intelligence course).

V. Results

We measured how accurately and how many times people taught each dance to the robot. The resulting data suggest that participants that taught the robot with a coherent model of emotion demonstrated the dances more frequently and more accurately than those that were asked to teach a robot with randomized emotional responses.

For every dance, on average, participants in the coherent emotion group chose to demonstrate the dance more often than those in the randomized emotion group. (Figure 6a.) The mean number of demonstrations per dance of participants in the coherent emotion group (5.1 dances) was significantly higher than the mean of the randomized emotion group (3.8 dances). ($p < 0.001$)

Each dance was also more accurately demonstrated on average by participants in the coherent emotion group. (Figure 6b.) The mean accuracies between the groups (coherent emotion: 82.6%; randomized emotion: 77.8%) were also significantly different. ($p = 0.002$)

In the survey, we asked participants to rate how believable the robot's emotional responses were on a scale from one to seven. (Figure 7a.) The difference between groups was significant. ($p < 0.001$)

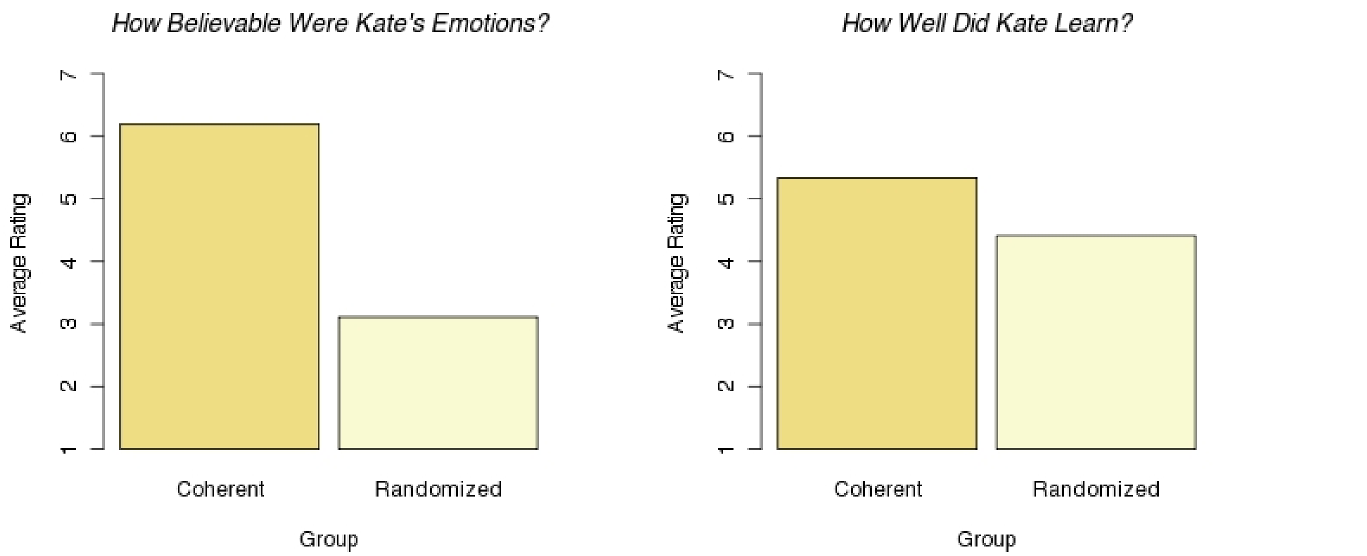
We also asked how well participants believed the robot learned (Figure 7b), which also produced a significant difference in means between groups. ($p = 0.04$)

VI. Discussion

A. Behavior Results

We hypothesized that a robot that displays coherent emotional responses will better engage participants tasked to teach that robot than one that displays randomized emotional responses, even if the robots' rate of learning and its scores were held constant between groups. We chose frequency and accuracy as measures of engagement with the teaching task, and in both measures we find significant differences between the groups. People did, on average, demonstrate dances more accurately and more frequently when the robot's emotional responses were coherent.

The frequency data has the strongest trend. In Figure 6a, we see that the range of average number of demonstrations per dance is non-overlapping between groups: the coherent emotion group ranges from 4.6 demonstrations of the first dance to 5.8 demonstrations of the last and the randomized emotion group goes from 3.4 demonstrations of the second dance to 4.2 demonstrations of the first dance. We believe this



(a) Average survey response to: **Kate's emotional responses seemed...** from **arbitrary (1)** to **believable (7)**. $p < 0.001$.

(b) Average survey response to: **Overall, Kate learned...** from **very poorly (1)** to **very well (7)**. $p = 0.04$.

Fig. 7. Participants rated the coherent emotional response case significantly more believable. Even though the robot's dancing and her scores were the same between groups, participants in the coherent emotion group thought that, overall, the robot learned better than those in the randomized emotion group.

data implies strong support for the existence of an effect of a coherent model of emotion.

We also find intriguing the steady rise of the average number of demonstrations per dance by the participants in the coherent emotion group. Some of this trend can be explained by the scores the robot earns: in the last two dances the robot earns good scores only after four and five repetitions respectively, whereas the participant need only demonstrate a dance three times to earn good scores in earlier dances. The robot's scores are approximately identical across the first three dances, however, and despite that, participants seeing the coherent model increased the number of demonstrations they provided from the first dance to the second, and from the second to third. We suppose this may be an indication of the participants' investment in the robot's success: participants may have wanted to see more improvement with each subsequent dance, so they demonstrated each successive dance more frequently.

The robot earns good scores after the third demonstration of the first three dances, after the fourth demonstration of the fourth dance, and after the fifth of the fifth dance. In the frequency data, we see that, on average, participants in the coherent emotion group were patient enough with the robot to demonstrate the dances until the robot achieved a good score on every dance. However, the participants in the randomized emotion group, on average, did not have the patience to demonstrate the dances enough for the robot to earn good scores on the fourth and fifth dances. We believe this indicates support for our hypothesis that the coherent emotional response group was more invested in the robot's success than the control group.

Among the number of demonstrations by the randomized emotion group, we see a sharp decrease from the first dance to the second. We suppose this may be reflect discomfort some participants in the randomized emotion group reported in their survey responses. We see this drop as an indication of loss of interest in the dancing task.

In the accuracy data, in the second, third, and fourth dances we see a significant difference in average accuracy between groups. ($p = .01$, $p = .04$, $p = .02$, respectively.) Although the trend is consistent across all the dances, we don't see statistically significant differences between groups in the first or fourth dance. We suspect this is a result of insufficient statistical power for these claims rather than some shared characteristic between these two dances. A contributing factor to the results in the first dance is a period of acclimation to the emotional responses – for instance, the very first demonstration of the very first dance happens before the participant sees any of the robot's emotional responses.

Curiously, three participants, all in the randomized emotion group, at some point during the interaction, stopped dancing altogether or purposefully made mistakes in their demonstrations. We suppose that these instances occurred only with the randomized emotion robot because of a lack of investment of these participants; these participants may have felt free to disrespect the robot because her emotions were not meaningful. One such participant reported feeling strongly deceived by the robot.

B. Survey Results

We hypothesized that, even without specifically drawing their attention to it, participants would make note of the robot's emotional responses. The survey data (Figure 7a) supports that conclusion and provides us verification of the perception of the differences between groups. This finding reinforces the behavioral differences between the two groups.

Even though the robot's rate of learning was identical for all participants, the survey data (Figure 7b) indicates that participants in the coherent emotion group believed she learned better, on average, than those in the control group. This result may be due simply to the relative patience of the coherent emotion group – they performed more demonstrations and consequently earned higher scores, so it would come as no surprise that they believe the robot learned better overall. This view suggests that the coherent emotion model yields a better impression of the robot's learning simply as a product of the patience that the coherent emotional responses instilled in the participants. From that we can claim that robots that display consistent and coherent emotions will not only see more and better teaching, but also will be more favorably judged in the process of learning.

Alternatively, perhaps the emotional responses altered the impression of the rate of learning the participants ascribed to the robot. Perhaps consistent emotions made the robot seem more sophisticated. Perhaps arbitrary emotions had the opposite effect. In either case, we can claim that the emotional responses of the robot made a significant impact on the impression of her ability to learn.

VII. Conclusion

We set out to explore the benefits of a consistent and coherent emotional model for human-robot interaction, specifically as it influences people who teach robots. We found that people who teach a robot expressing consistent emotions are more engaged in teaching the robot to dance than those who teach a robot expressing emotions that aren't appropriate to the situation the robot is in. People's enhanced engagement with the coherent emotional response robot is supported both by their more accurately demonstrating the dances to be learned and by their providing more demonstrations to the learner.

Our findings suggest to human-robot interaction designers that certain interactions will benefit from, perhaps even depend on, endowing robots with believable emotional responses. Arbitrary emotional expressions are not sufficient to sustain engagement; emotion must be consistent with the state of the interaction.

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