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How Happy Should I be? Leveraging Neuroticism and Extraversion for Music-Driven Emotional Interaction in Robotics

Richard Savery, Amit Rogel, Lisa Zahray and Gil Weinberg

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10.1 Introduction

Emotion in robotics covers a broad range of uses, from enhanced social interaction [35] to improved survivability and performance [2]. Personality has also been utilized in human robotic interaction research, such as in works that embed human personality in a robot to drive certain reactions and uses [21]. Another common approach is using human personality to understand robot perception, such as the overall impact of the uncanny valley [28]. While emotion is considered a critical feature of personality and is intertwined with the definition of personality itself [40], less research has been conducted addressing the interaction of personality, emotion, and robotics. We contend that sound and music, is intrinsically emotional and tied to human personality, and an effective medium to explore the relationship between each area.

In this work, we consider links between two of the Big Five personality types, Neuroticism and Extraversion, their impact on human emotional responses, and how these traits can be leveraged for HRI. The Big Five is the most common measure of personality in psychology [12,38] and is considered cross-cultural [30] with each trait representing discrete areas of the human personality [58]. The personality traits in the Big Five, also known by the acronym OCEAN, are Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Here, we focus on Neuroticism and Extraversion, which have shown robust and consistent findings in regards to their role in emotion regulation for a human's personality [3]. These personality traits lead to emotion strategies such as the human process of exerting control over the intensity and type of emotion felt and how that emotion is displayed [16].

We contend that human personality strategies for emotion can be used to drive design choices for robot emotional responses. A human's personality traits can lead to unique approaches to emotion; for example, individuals with low levels of extraversion are much more likely to outwardly display lower valence emotions. We believe that by mimicking human emotion strategies that are drawn from personality models, we can create varying versions of robotic responses to stimuli. By modelling human responses to emotional stimuli we can create robotic personas that are perceived differently by human collaborators.

In this work we developed two separate emotional responses to positive and negative stimuli, projected through audio and gestures. These personality types are based on human emotion strategies for different levels of Neuroticism and Extraversion. We believe that emotion strategies can be leveraged to portray varying robotic personas, with each persona receiving different ratings from human participants. We propose that through duplicating consistent emotion strategy from the Big Five framework, robots will achieve higher likeability and improved collaboration metrics than a control group.

For the study, we embedded custom emotional gestures and emotional musical prosody (EMP) in an industrial robotic arm. We believe robotic arms are especially well positioned to benefit from increased social interaction through audio and gesture, as they lack facial features and other communication methods often present in social robotics. The robotic gestures used were based on human body language poses and were validated before use. The audio system was based on an emotional musical prosody engine that has been shown effective for robotic arm interaction [45]. Avoiding speech and language has many advantages when it is not required for the interaction, such as reduced cognitive load [56] and improved trust [43].

This study aimed to address two key questions, firstly how a robot's personality type, as portrayed through emotion regulation strategies alter the perception of the robot. The second question aims to understand if a users' personality alters their preference for robot emotion regulation strategies. The study found that ultimately all users prefer robots with low neuroticism and high extraversion and that music and gestures is an effective medium to portray emotion in a robotic arm.

10.2 Background

10.2.1 Emotion and Robotics

Emotions can be classified in a variety of manners. The most common discrete categorization as proposed by Ekman [13] includes fear, anger, disgust, sadness, happiness and surprise. Emotions can also be classified by a continuous scale such as the Circumplex model; a two-dimension model using valence and arousal [39]. Research in robotics and emotion has seen continued growth across the last 20 years [44] and can be divided into two main categories – emotion for social interaction, and emotion for improved performance and "survivability" [2]. For social interaction, emotion can improve general expressiveness and interaction metrics [31]. For improved performance or survivability, robots can use emotion to reinforce or correct actions such as improved navigation [57].

10.2.2 Personality and Robotics

There are a variety of frameworks for the analysis of human personality in psychology literature, with the most common categorizations classifying personality between three and seven traits [23]. In human robot interaction literature, the term personality is not always used consistently and often lacks an agreed upon framework [41]. It is relatively common for HRI researchers to describe robot personality based on distinctive responses to stimuli, without basing their work on any specific personality model [6, 32]. Some studies have shown the potential of embedding psychologically driven personality models in human robot interaction [48]. These include aligning human and robot actions based on human personality [51], predicting the acceptability of a robot in a teaching environment [9], and understanding the impact of personality on understanding robot intentionality [7].

The Big 5 has been used previously in robotics, such as work focusing on extraversion and introversion in medical settings [49]. Other work has demonstrated human participants could accurately identify whether a robot was acting as an introvert or extrovert [27]. General attitudes based on a human's personality traits to robots has also been studied [34]. Likewise, past studies have shown that humans identify personality traits on robots, with general preferences emerging for positive traits [53]. Emotion modeling has been incorporated into some robotic personality models. For example, [1] use custom, subjective variations in emotional response to create nine unique personalities. [47] and [36] developed a robotic personality based on the Big Five, while using emotional responses based on possible relations between each class of the Big Five and emotion.

10.2.3 Emotion Regulation Strategies for Robotics

Emotion regulation is the process of attempting to modify both an internal feeling of emotion and our external expression of an emotion [15]. There are three core features of emotion regulation that separate regulation from common approaches to emotion in robotics. The first is regulation relies on an intrinsic or extrinsic activation of a goal to modify emotions [17]. The second feature emphasizes attempting to mentally engage with the cause of the emotion and changing one's internal reaction [18]. The third feature relies on varying the length and intensity of an emotional reaction [50].

Emotion regulation is a key element of emotion in humans and has direct links to personality, and has been hardly addressed in HRI research. Research has begun to cover potential deep learning applications for creating emotion regulation [19], strategies, however these have focused on generative processes and not human applications. A meta-analysis of emotion regulation and the Big Five found 32,656 papers including reference to regulation strategies linked to personality [4]. These findings are not always consistent however both Extraversion and Neuroticism had robust findings across the survey.

Overall, the literature in human psychology strongly indicates that emotion regulation strategies can be linked to personality traits for high Neuroticism and low Extraversion or low Neuroticism and high Extraversion in humans. [37] in particular, describe contrasting response types for positive and negative emotion. High Neuroticism and low Extraversion (HighN-LowE) personalities are consistently more likely to respond to positive stimuli with lower valence emotions, such as relief, whereas low Neuroticism and high Extraversion (LowN-HighE) are much more likely to respond directly with Joy or Happiness. For negative stimuli, HighN-LowE have a much higher likelihood to show disgust, fear, or guilt, while LowN-HighE are more likely to express sadness. In this paper, we utilize these approaches to present a LowN-HighE robot and a HighN-LowE robot, each capable of responding with a different range of emotions to stimuli. This creates personality models that are able to respond to positive or negative stimuli, with varying response types, allowing a positive response to take multiple forms.

10.3 Stimulus

To present models of emotional strategies, we developed and embedded gesture and audio based interactions in an industrial robotic arm. Our experiment design consisted of emotional robot gestures and responses to tagged image stimuli, followed by text questions. These responses were emulated from a study of response to visual stimuli with human personality types in existing research [37].

We chose to use a robotic arm due to its rapid expansion in use, with expected growth continuing into the foreseeable future, largely due to factory and industry settings. Research has also shown that embedding emotion driven gestures and audio in non-anthropomorphic robotic arms is more effective in portraying affect, than embedding such gestures and audio in social robots [45]. Our stimulus was designed as arm gestures that would respond to emotion tagged images in a manner derived from the personality traits.

10.3.1 Emotional Musical Prosody

We utilized an existing music-driven vocal prosody generator designed to represent emotions in audio [46]. Emotional musical prosody contains audio phrases that do not have semantic meaning, but are tagged with an emotion. They are useful in environments where sentiment or alerts are required from sound, without semantic meaning. The model we used included validated emotional phrases that use a voice-like synthesized processed sound. The dataset was labeled using the Geneva Emotion Wheel (GEW) [42], which combines both a continuous classification approach based on valence and arousal as well as discrete labels. The model lists 20 distinct emotions over a circle, with positions corresponding to the circumplex model of affect [39]. Each quadrant of the GEW corresponds to a different high/low valence-arousal pair, with arousal on the vertical axis and valence on the horizontal axis. The GEW emotions also correspond to the emotions linking HighN-LowE and LowN-HighE, allowing us to use the classification directly in a personality model.

10.3.2 Gestures

To physically display emotion strategies we used the generative system described in Chapter 13, mapping human gestures to a 7-joint robotic arm. The movements for each joint were created by hand, the guidelines and matching our emotion driven musical prosody engine. The gesture system was designed by studying traditional human body language postures. Human gestures were broken down into their fundamental movements based on [52] and [11]. These motions were then mapped to various joints on the robot. Most of these mappings involved designing erect/collapsed positions for the robot as well as forward/backward leaning motions to create a linear profile of the robot that matched human gestures.

While human gestures informed the robotic arm's movement speed, rest times between movements and number of movements were designed to synchronize with the audio phrases to create a connection between the emotional prosody and the physical movements of the robot. After primary joint movements were established, smaller, subtle movements were added to some of the remaining joints to increase the animacy of the robot.

Video samples with audio are available at https://soundandrobotics.com/ch10

10.3.3 Validation

Human perception of the robotic gestures and sounds used in the experiments was validated in a user study. Each participant completed a survey containing 30 videos. Each video was approximately 8 seconds long and depicted a robot gesture and sound corresponding to a particular emotion. 17 different emotions were represented among the videos, chosen due to the emotions used in personality based-responses. After each video, participants were asked to identify the emotion they perceived, along with its intensity on a scale of 1-5, using the Geneva Emotion Wheel. One video was used as an attention check, which showed a robot gesture along with audio instructing the participant to select a particular choice. The validation used a total of 20 participants from Amazon Mechanical Turk. One participant was eliminated due to failing the attention check, leaving a total of 19 valid participants. Of these, there were 11 from the United States, 6 from India, 1 from Thailand, and 1 from Malaysia. 17 identified as male, and 2 as female. The mean age was 36.5. The gestures and audio had previously been validated independently (only audio and only gestures), which we believe allowed us to test only a small group.

We utilized two metrics to analyze the validity of the videos, based on [10] – the mean weighted angle of the emotions reported by participants and the respective weighted variance. Both of these metrics were weighted according to reported intensity, and were converted to units of emotions on the wheel. The average emotion error (absolute difference between weighted reported emotion and ground truth emotion) was 1.7 with a standard deviation of 1.1. The average variance was 2.8. All emotion errors were below 3.5 except for one video, which represented admiration and had an error of 5.0. These results show that participants were able to interpret the expressed emotions within a small range of error, making the videos suitable for use in the experiments.

We believed the emotion error rate was well within a reasonable rate for this study. The error of 1.5, with a standard deviation of 1.1 showed that even when participants did mistake an emotion for another, they were usually only one emotion off, which was within the range of a possible response in our personality model.

10.4 Experiment

10.4.1 Method

Research question 1 examines how the robot's personality alters its perception amongst all participants. This question does not consider the participants' personality type and instead aims to identify broad trends amongst all interactions. We considered the traits or anthropomorphism, animacy, likeability, and perceived intelligence for each robot.

Research Question 1) How does a robot's personality type as portrayed through emotion regulation strategies alter anthropomorphism, animacy, likeability, and perceived intelligence?

We hypothesized that the robot with LowN-HighE will achieve greater ratings for likeability and perceived intelligence, while we will see no difference in anthropomorphism and animacy across all participants combined. We believed that emotion regulation strategies matching LowN-HighE are conducive to immediate likeability in a short term experiment as they show less unpredictability. We believed predictability will also contribute to an increase in perceived intelligence.

Our second research question considered the effect a users' personality will have on how they interact with the robotic arm.

Research Question 2) How does a users' personality type impact their ratings of different emotion regulation strategies for anthropomorphism, animacy, likeability and perceived intelligence?

We hypothesized that each category will have a preference for the emotion regulation strategy that matches their own personality type for likeability and perceived intelligence, while there will be no difference for anthropomorphism and animacy. While the previous question described our belief that LowN-HighE would achieve better results, overall we believe that would occur largely to the addition of LowN-LowE or HighN-HighE, whereas each group individually will show significant variation in results.

Participants first read a consent form and entered their names to confirm consent. They then completed the Ten Item Personality Measure (TIPI) [14], which gives the users' personality with the Big Five emotion model. TIPI was chosen as it has shown strong convergence with widely used longer measures, and has been shown to effectively gather personality in online platforms such as Mturk [8].

The main section of the experiment involved participants seeing a photo followed by a robotic response. We used photos from the open effective standardized image set (OASIS) [26], which features a range of images tagged with valence and arousal ratings. We chose photos that clearly showed positive or negative sentiment but also with a high standard deviation still within the bounds of positive or negative, implying a range of emotional response. We used a between experiment design, with participants randomly split into two groups, either seeing a robot responding to the stimuli with LowN-HighE or a robot responding with HighN-LowE. The responses were based on the response type described in Section 10.2.3, with each image returning an emotion based on the varying emotion regulation strategies. The same images were used for each robot personality type.

Figure 10.1 shows a sample sad image with a still of the robotic response. For each photo participants were asked to identify if the accompanying emotional reaction matched the image with a yes, no, or "other" option. This was inserted to force participants to watch, as every expected response was yes. Stimuli were randomly ordered for each participant with an attention check also appearing randomly. The attention check involved a related image as well as audio requiring the participant to type a specific phrase in the selection box "other".

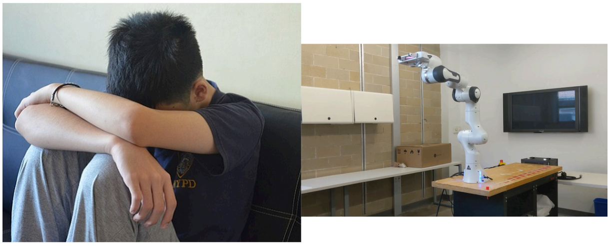

FIGURE 10.1
Sample stimulus and still of robot response.

Following reviewing the emotion stimuli participants were shown three text questions with an accompanying emotional response. The responses to each question were matched to expected responses by personality as found in work by [37].

1. How stressful was the task you just completed?
2. To what extent did you experience positive emotions?
3. To what extent did you experience negative emotions?

After viewing all stimuli, participants completed the Godspeed Questionnaire. Participants were asked to complete the survey while considering the robot across all videos shown for each image. Godspeed is a commonly used human–robot interaction standard for measuring anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots [5]. We chose not to ask participants about perceived safety as felt it was not relevant to the research question or reliably observed given the experiment design. The Godspeed Questionnaire involves 28 questions (22 without perceived safety), rating users' impression of a robot for terms such as Artificial to Lifelike, which combine to give the broader metrics. Following the Godspeed test, we collected participant demographic information including year of birth, country of origin, and gender. The combined study took no more than 15 minutes, with the average time to completion of 11 minutes. The survey form was hosted on Qualtrics.

We had 100 participants complete the study on MTurk, of which 8 were eliminated due to failing an attention check, leaving a pool of 92. Of the 92 participants, the mean age was 42 with a standard deviation of 10 and a range of 22 to 69. 36 participants identified as female and 57 as male. Each participant was paid $2.00. 21 participants' country of origin was India, with the other 71 from the United States. We found no significant variation in responses from differences in countries of origin, gender or age.

This study was performed online using pre-recorded videos instead of live interaction or video watching in person. We believe that for this experiment this was an acceptable experimental design as ultimately our analysis focused on external viewing and analyzing a group of robots. Multiple past papers have shown no significant variation in results when a participant is watching a robot on video compared to in person [54, 55]. We also believe the use of MTurk and Prolific has some advantages over in person studies, allowing us a far larger and more diverse participant pool than possible in person. It has also been shown that compared to university pools, MTurk participants are more careful [20]. When combined with our multiple point attention check we are confident that our results would be replicated in person.

10.4.2 Results

We first analyzed the participants' personality results and found the break down between Neuroticism and Extraversion as HighN-HighE $n{=}11$, LowN-LowE $n{=}13$, HighN-LowE $n{=}27$, and LowN-HighE $n{=}36$. For the Godspeed test, we first calculated Cronbach's Alpha for each category. The results for each category were: Animacy *0.83*, Anthropomorphism *0.88*, Likeability *0.92*, and Intelligence *0.91*. This indicates a high internal consistency across all survey items.

10.4.2.1 Research Question 1

The robot personality with LowN-HighE emotion responses had a higher mean for both likeability and perceived intelligence. After conducting pair-wise t-tests the results were significant for both categories; for likeability ($p = 0.011$) and for perceived intelligence ($p = 0.015$).

For likeability LowN-HighE the results were *(M = 4.191, SD = 0.684)*, with a confidence interval of *(3.903, 4.480)*. LowN-HighE had a high effect size of 0.856. HighN-LowE had *(M = 3.606, SD = 0.924)* and a confidence interval *(3.272, 3.940)*. For the intelligence statistics LowN-HighE had *(M = 3.992, SD = 0.790)* and the confidence interval *(3.658, 4.325)*. LowN-High had a high effect size of *0.741*. For intelligence HighN-LowE had *(M = 3.406, SD = 0.919)* and the confidence interval *(3.074,3.737)*. For anthropomorphism and animacy the results were not significant ($p \geq 0.05$). These results proved our hypothesis and showed that the robotic personality type did alter the general populations' ratings for likeability and perceived intelligence. Figure 10.2 shows a box-plot of the results.

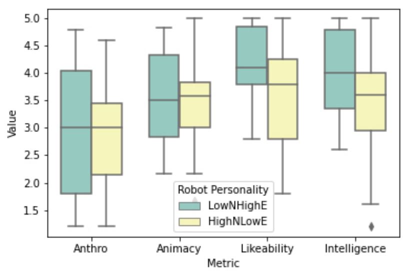

FIGURE 10.2
Comparing robot personality across all participants.

10.4.2.2 Research Question 2

Both human personalities rated the robot with LowN-HighE higher for likeability, with a pair-wise t-test giving significant results for LowN-HighE ($p{=}0.025$) but not for HighN-LowE ($p{=}0.147$). Figure 10.3 shows an overview of these results. This partly supported the hypothesis with LowN-HighE preferring LowN-HighE, but without significant results for HighN-LowE. Likewise perceived intelligence rating was higher from both for LowN-HighE, but again only with significant results for LowN-HighE human personalities ($p{=}0.049$), and for HighN-LowE ($p{=}0.78$).

Contradicting our hypothesis both animacy and anthropomorphism showed ratings for robot personality that matched that of the human personality. Users with LowN-HighE rated the robot with LowN-HighE better for both animacy and anthropomorphism although neither was significant ($p \geq 0.05$). HighN-LowE also rated animacy and anthropomorphism higher for the robot with HighN-LowE, with a significant result for anthropomorphism ($p = 0.004$).

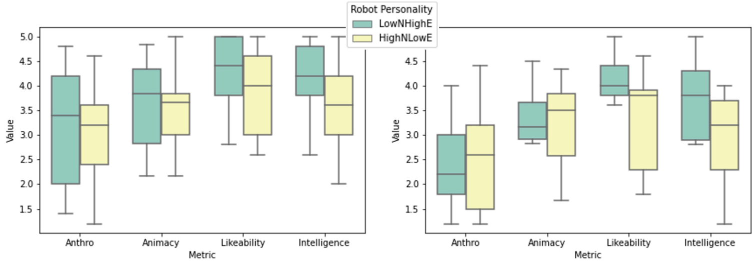

FIGURE 10.3
Comparing human personality across platform. Left indicates humans with LowN-HighE, right HighN-LowE.

Further discussion of these results is available in Section 10.5, including comparisons with the results from our second experiment.

10.4.3 Supplementary Results: Openness, Conscientious and Agreeableness

Our research questions focused on collecting and analyzing the personality traits Neuroticism and Extraversion, however standard personality measures for the Big-5 also include Openness, Conscientiousness and Agreeableness. Openness is linked to levels of curiosity and willingness to try new things; conscientiousness is considered a efficiency and organization, while agreeableness is related to friendliness and compassion. As previously described these traits do not have consistent findings in relation to emotion regulation, nevertheless we believe analyzing the links between human's ratings for openness to our other variables is worth consideration to guide future work.

Our results for human Openness to experience matched expectations, with the more open a participant the more likely they were to rate both robot personalities as likable and intelligent. Comparing openness and intelligence gave a Pearson's correlation coefficient of *0.4* with p=*0.002*, indicating a moderate positive relationship. Figure 10.4 shows the high and low openness trait for each metric.

While [8] found Mturk personality surveys gave accurate results, we believe TIPI was insufficient for measuring conscientiousness and could not draw any conclusions on the trait. TIPI includes two questions for measuring conscientiousness, asking for a self-rating of participants' dependability and carefulness. For Mturk we believe participants would be wary to mark either rating too low and risk their rating on the platform. This lead to a distribution with 88 participants rating themselves as highly conscientious and 5 giving themselves a low conscientious rating.

We found no relation between agreeableness and preferences for emotion regulation or robotic personalities. The Pearson correlation coefficient for each

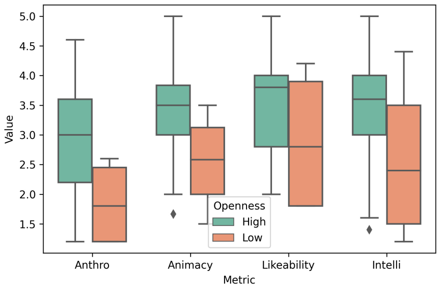

FIGURE 10.4
Openness to experience personality trait rating for each metric.

metric was: animacy (0.136, *p=0.195*), anthropomorphism (0.46, *p=0.661*), likeability (0.195, *p=0.062*), and perceived intelligence (0.190, *p=0.069*).

This replicates common psychology findings, that find agreeableness plays a part in emotion regulation near exclusively in social emotion settings [24,25,29].

10.5 Discussion

10.5.1 Human and Robot Personality

We found LowN-HighE consistently more likable for all users, with significant results for the LowN-HighE human with LowN-HighE robot. While we can not conclude why this is the case, we believe it may be due to the nature of short-term interaction. Especially in a single encounter, it is reasonable to assume that a robotic agent that shows higher extraversion and more emotional stability (through lower neuroticism) is more immediately likable regardless of a user's personality.

LowN-HighE also received higher ratings for perceived intelligence across both personality classes. This indicates that perceived intelligence is much more than just the ability to accurately complete a task. All users almost unanimously rated the robot as correctly identifying the emotion, yet still found a significant difference in perceived intelligence. As for likeability, we believe this reduced intelligence rating is due to higher levels of emotional instability.

Contradicting our hypothesis anthropomorphism and animacy ratings corresponded to human personality types, with HighN-LowE and LowN-HighE both rating their matching robotic personality higher. While we did not predict this, we believe this does make sense as users who see emotion regulation strategies closer to their own may be more likely to see anthropomorphic characteristics in a robot and more lifelike behavior.

10.5.2 LowN-LowE, HighN-HighE

Our core personality design involved HighN-LowE and LowN-HighE, however in our participant pool we had users with these personality traits. For this reason we include some preliminary findings on the group. Our sample size from experiment one was significantly smaller for both these groups (n=11 and n=13). Figure 10.5 shows the results for all personality types. LowN-LowE and HighN-HighE personalities are less common and less easily grounded in literature, so any conclusions from this data are not easily verified. However, there are some clear distinctions between comparisons of each human personality. HighN-HighE has almost no variation between robot personality with no significant results. This implies either that emotion regulation strategies do not impact this personality type, or that neither of our emotion regulation strategies strongly impacted HighN-HighE personalities. LowN-LowE personalities however did not have significant results for the LowN-HighE robot, for perceived intelligence (*p=0.48*) and likeability (*p=0.49*). This matches the results achieved for the general population and the LowN-HighE group. Despite these results, there is still future work required to draw any conclusions about LowN-LowE and HighN-HighE personalities and robotics.

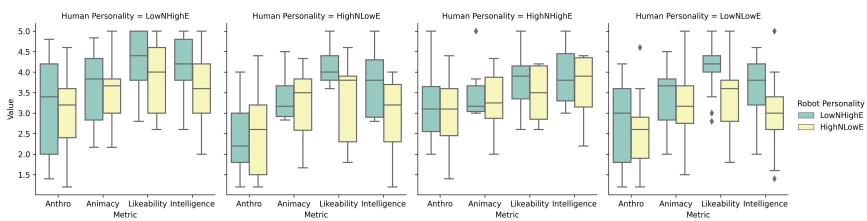

FIGURE 10.5
Comparing LowN-LowE and HighN-HighE.

10.5.3 Limitations

While attempting to control for all weaknesses in the study, there are several limitations that are worth describing. We did not collect information on participants on how they perceived the personality of each robot, so do not have a firm metric that the robot was believed to be a certain personality. This however was a considered decision; it has been repeatedly shown that untrained humans are inaccurate at predicting other human's personality types through observation, especially over short interactions [22, 33], so there is no reliable way to gauge whether a personality type was perceived by a human user. Additionally emotion, while a strong part of personality, is just one component; we do not make a claim that we fully captured any personality trait, instead our goal was primarily to leverage features of personality traits and emotion. Nevertheless, future work attempting to identify how emotion regulation in robotics portrays a personality type to users would be of benefit.

Our study used videos of the robots interacting instead of in person participation. We believe for this experiment this did not alter the end results and improved overall outcomes as we were able to recruit many more participants than would be possible in person. Multiple past papers have shown no significant variation in results when a participant is watching a robot on video compared to in person [55]. In future work, we expect to apply lessons learned from these studies to in person experiments and interactions and believe lessons learned from video will apply to in person studies.

10.5.4 Future Work

This research will enable three new directions in future robotic research. The first is extended research in robot customization, based on a human's personality type. This can not only include audio features as described in this paper but also consideration of all areas of robotic design. We envision future studies where robot personalities are adapted in the short-term and over longer use, to the personality traits of individual users.

The second key area is robotic customization to task and project goals, building through the lens of robotic personality. By embedding personality traits in robots through design variations we believe robotics can be better developed for specific interactions and human experiences. There are times when a higher neuroticism level displayed through audio and gesture may be useful, such as times when robot interactions should not be the immediate action.

Finally, we believe this research outlines the need for further consideration and research of personality traits and their links to human robot interaction. While this was only an early step into the role of personality traits and potential links, future steps focusing on embedding specific personalities into robotics can lead to many enhanced outcomes. Using human personality preferences to design robotic emotional responses can have multiple broader implications. Emotion regulation strategies for a robot, whereby the strength of emotional response to stimuli are altered by a personality based design framework, provides the opportunity to drive new areas in human–robot interaction and develop new knowledge regarding the mechanisms that underlie affect based interaction. Developing an understanding of the potential of personality and emotion informed design can lead to the creation of deeper interactions between humans and robots and inform the development of a new framework for emotion driven interaction

10.6 Conclusion

The paper presents a new framework for developing emotional regulation and personality strategies for human–robot interaction through the use of sound and gesture. It explores how the Big Five personality traits can inform future designs of emotion-driven gestures and sound for robots. In particular, it studies the interplay between human and robotic Neuroticism and Extraversion and their effect on human perception of robotic personality. Key contributions include the development and implementation of novel affect and personality models for non-anthropomorphic robotic platforms. Other contributions include a groundwork understanding of emotion regulation strategies in human–robot interaction and novel insights regarding the underlying mechanism of emotion and affect in robotics.

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