Emotion in Motion: Exploring User-Defined Emotional Perception in Non-Anthropomorphic Robots

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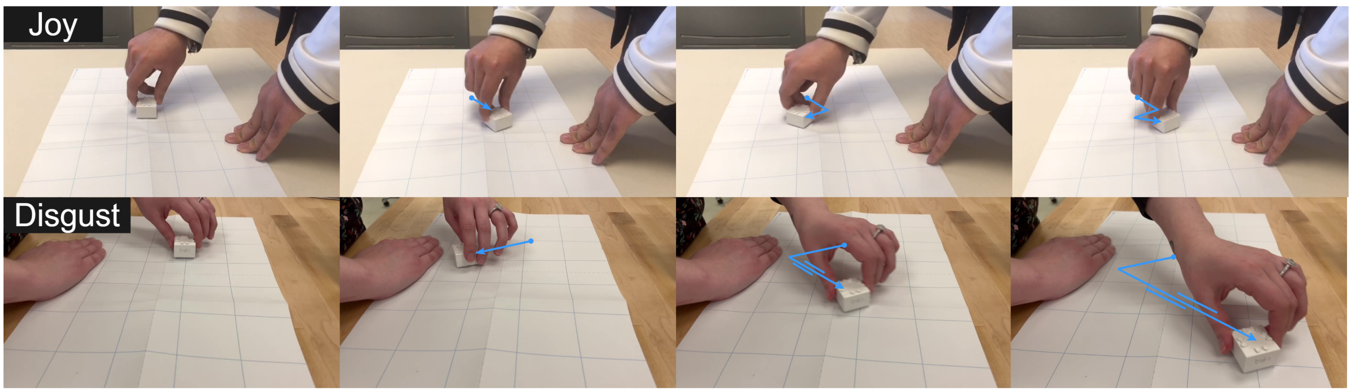

Figure 1: Emotion in Motion is an elicitation study on how people use movement to model emotions in non-humanoid robots. Participants hand-controlled a Toio robot. Above are examples of how participants may model joy by zigzagging or disgust by approaching the user and quickly moving away.

ABSTRACT

The lack of human-like physical features in non-anthropomorphic robots presents a challenge in human-robot communication since humans often rely on visual cues like facial expressions and body language to understand emotions. To address this challenge, this elicitation study explores user-defined movements that correspond to specific emotions, thereby advancing our understanding of human perception of emotion conveyed by non-anthropomorphic robots. Through analyzing the movements of a Sony Toio robot ideated by participants to model a specific emotion, we identify general patterns of movement and generate a set of user-defined motions for emotional expression. The results of this study provide insights for the development and design of non-anthropomorphic robots in social settings and improving human-robot interactions through motion-based emotional expression.

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CCS CONCEPTS

• **Human-centered computing** → **User studies**.

KEYWORDS

Non-anthropomorphic; robot; emotion; motion; movement; elicitation

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1 INTRODUCTION

The field of human-robot interaction has seen significant advancements in recent years, with a growing focus on developing more emotionally expressive robots [12]. Since emotions are a vital aspect of human communication, emotional expression in robots can facilitate more natural interaction with humans while also conveying information about the robot's internal state [7, 33]. The use of non-anthropomorphic robots, which lack human-like physical features for expression, presents a unique challenge in this area. These robots may struggle with effectively conveying emotions to humans, which can cause a disconnect in communication.

Motion is one of the primary modalities non-anthropomorphic robots can use for communication. The movement of a robot can help convey its intentions and internal state [7]. Furthermore, people tend to attribute emotions to a robot's movements, which can significantly impact the quality of their interaction by influencing the perception of the robot's likability, trustworthiness, and overall pleasantness [33]. However, establishing the motions associated with an emotion is a challenging task due to various factors, such as a robot's physical limitations and the complexity of human emotions, including cultural differences and individual variations.

This study seeks to address this challenge by conducting an elicitation study to explore the connection between user-defined movements and the emotions conveyed by a robot.

In this study, participants were tasked with generating movements for 8 different emotions using a small non-anthropomorphic robot (Sony Toio) controlled by hand. Originally, the Toio was to be controlled through touch-screen but an expert advised that controlling the robot by hand may be better for modeling emotions than controlling it through touch-screen. The user-defined motion and key metrics (e.g., distance and speed) were recorded and analyzed to extract important features from the movements that correspond to each emotion. The analysis will provide insights into the participants' abilities to communicate emotions through these robots and inform the development of more emotionally expressive non-anthropomorphic robots.

The emotions chosen in this study comprise of the 8 basic emotions (anger, anticipation, joy, trust, fear, surprise, sadness, and disgust) identified in Plutchik's model for emotional classification [23]. Prior related work often uses Ekman's 6 basic emotions (anger, surprise, disgust, enjoyment, fear, and sadness), which is a smaller subset of the emotions identified in Plutchik's model. [8, 12] This study and other related works use these emotional classification models as a practical tool for organizing the complexity of emotions. However, it is important to acknowledge the limitations of emotional classification models which may impact their accuracy and applicability. This includes a lack of universality by assuming emotions can be discretely categorized regardless of cultural and individual differences, possible oversimplification of the complexity and variability of emotion, and the lack of empirical evidence to support their validity despite being widely cited and used [2].

The findings of this study have important implications for the design and development of non-anthropomorphic robots in social settings. By better understanding the relationships between movements and emotions, we can strive to enhance communication between individuals and non-anthropomorphic robots by utilizing emotional expression through motion. The main contributions of this work are:

- Identifying the emotional perception of various robot movements.
- Insight into general user preferences for designing motion-based emotional expression in non-anthropomorphic robots.

2 RELATED WORK

In this section, we discuss relevant categories of related work: anthropomorphic robots, emotionally expressive non-anthropomorphic robots, and elicitation studies.

2.1 Emotional Expression in Anthropomorphic Robots

Prior work in emotional expression in robotics has largely focused on anthropomorphic robots. Research in anthropomorphic robots and emotion focuses on developing effective strategies to elicit emotional responses from users through robot behaviour. However, it is important to consider that each robot has a unique design and construction, which may require different approaches to communicate emotions effectively.

The form of a robot is a crucial factor in determining how it can effectively express emotions. Anthropomorphic robots often have an advantage in using body language to convey emotions because they can directly mimic human gestures and movements. There exists a wide range of literature that investigates emotional expression using motion in humanoid robots, exploring everything from the movement of a robot's head to the gait of a robot [19, 30]. Marmpena et al. [21] delved into how humans perceive emotions expressed through the body language of the Pepper robot, finding that people could accurately identify the valence and arousal of emotions conveyed. However, slight differences in the form of a humanoid robot can affect how their emotional expressions are perceived. Erden [9] found participants had more difficulties identifying emotions in the body language of the Nao robot compared to robots with more degrees of freedom. Furthermore, the joint angles and movements used to convey emotions in the Nao robot were not directly applicable to other robots. Our study recognizes the importance of considering a robot's unique physical characteristics in exploring emotional expression, and examines such expression in a robot lacking human-features.

Facial expressions also play a crucial role in non-verbal communication for humans and have been widely adopted by robots as a means of conveying emotions. In a study conducted by Herdel et al., it was found that incorporating facial expressions into social drones was an effective way to convey the drone's emotional state [15]. However, not all robots have the capability to display facial expressions and it is important to explore other communication modalities that are more common to all robots. Our study focuses on emotional expression using movement.

2.2 Emotional Expression in Non-Anthropomorphic Robots

For non-anthropomorphic robots, numerous studies have focused on exploring emotional expressivity in in zoomorphic robots [13, 25, 27, 29]. A study by Gácsi et al. found that people can correctly identify emotions of robots displaying dog behaviour. Similar results were found by Singh and Young by attaching a robotic tail to a Roomba. However, not all non-anthropomorphic robots possess animal-like features that facilitate such expression.

Other studies have explored communication modalities for abstract non-anthropomorphic robots. Song and Yamada explored emotional expression using color, sound, and vibration by creating various combinations of these modalities for a robot sphere [26]. Similarly, Löffler et al. investigated emotional expression using color, sound, and motion for a simple cylindrical robot [20]. Both studies found using multimodal expression improved emotion recognition, with color and motion being the most effective modalities [20, 26]. A few studies have also explored the use of haptics in emotional expression [16, 18, 32]. Hu and Hoffman demonstrated that touching a shape-changing robot is effective in conveying the valence (pleasantness) and arousal (intensity) of an emotion [16]. People can also accurately perceive emotions through small movements. Cuddlebits, a small non-anthropomorphic robot can convey emotions through breathing movements [4]. Additionally, Anderson-Bashan et al. [1] suggest that people could perceive minimal approaches and avoid gestures of an abstract robot as positive or negative opening encounters.

In terms of motion, Santos and Egerstedt [24] investigated the expression of emotions through swarm robot motion, focusing on non-anthropomorphic emotional studies that explore Human-Swarm Interaction (HSI). They address the challenge of integrating predefined motions and shapes associated with emotions into swarm behaviour and successfully map the resulting motions by asking participants to categorize them according to emotions. Further work with swarm robots and pre-defined movements by Dietz et al. found that speed correlated with arousal and smoothness of the motion with valence of the emotion [5]. Most previous literature focuses on the classification of emotions for predefined movements [3, 5, 14, 24]. In this paper, we explore user-defined movements for robot emotion.

2.3 Elicitation Studies in Human-Computer Interaction

Elicitation studies are a method of determining the preferences and expectations of the general population by collecting data on user-defined actions [28]. After data collection, user-defined actions are categorized based on similarity criteria producing a user-defined set [32]. Elicitation studies in HCI have often focused on gesture interaction [28, 32] and interaction techniques [32]. These studies come in different forms, and the approach used often depends on the research question. One common approach involves asking participants to choose actions from a predefined list. For example, the study conducted by Dim et al. [6], explored how blind individuals can interact with a TV using gestures by presenting participants with a list of predefined gesture choices and asking them to select the most appropriate gesture for a particular action.

2.3.1 Elicitation Studies in Human-Robot Interaction. In HRI, elicitation studies play a crucial role in improving the design and functionality of robots by exploring how humans and robots can effectively communicate [11, 17]. The main objective of these studies is to ascertain how users and robots interact in different scenarios.

Kim et al. [17] conducted an elicitation study to develop a user-defined set of control interactions for tabletop swarm robots. The study results showed that participants used a variety of interactions based on referents, number of robots, and proximity. Based on these results, the authors compiled a comprehensive interaction set based on the findings, which included using 1-2 fingers, one hand, and both hands depending on group size. In addition, Firestone et al. [11] conducted an elicitation study to improve the communication of small unmanned aerial systems (sUAS) states to end-users. The study recognized the general public's unfamiliarity with sUAS interaction and communication. It thus aimed to create an intuitive system that can quickly convey the state of the sUAS by classifying the movements proposed by participants.

Elicitation studies in human-robotic interaction have primarily focused on gesture interaction or action communication, with fewer studies examining user-defined emotional expression in robots. However, Zhou et al. [31] conducted an innovative elicitation study that explored how designers can effectively convey emotions through robotic touch. In this study, the authors developed a unique robotic haptic platform capable of mimicking human touch and asked 11 designers to create patterns for eight different emotions, including five of Ekman's basic emotions and three pro-social emotions. The results showed that designers employed various approaches to convey emotions, including adjusting the vibration intensity and pattern. Although this study focused on robotic touch rather than movement, it provides valuable insights into the possibilities for designing emotionally expressive robots through different modalities.

3 APPLICATIONS

The outcomes of our study hold considerable importance for advancing the design of non-anthropomorphic robots capable of accurately expressing emotions to users and audiences. Our research suggests that even robots with restricted degrees of freedom and non-humanoid forms can effectively communicate emotions. Below are examples of how our studies findings may have useful applications in the "real world":

3.1 Manufacturing

Non-humanoid robots could be helpful in manufacturing. A robot that expresses frustration or urgency can signal to human workers the importance of a task, helping to meet production deadlines. Additionally, by expressing sadness when detecting a defective product, a robot can alert human workers to the issue, allowing for prompt corrective action and improved quality control. Unlike humanoid robots, which are designed to resemble humans and can create unrealistic expectations of how a robot should behave [22], non-anthropomorphic robots do not have these preconceived expectations. This allows for more flexibility in their interactions with human workers.

3.2 Rehabilitation

In the field of rehabilitation, robots have been used for therapeutic interventions for individuals with social disorders like autism spectrum disorder [10]. Non-anthropomorphic robots that are able to express emotions can provide a safe and controlled environment for individuals to learn how to recognize emotions. In addition, non-anthropomorphic robots can be designed in a way that is more customizable to the specific needs and preferences of children with autism. For example, the robot could be designed with bright colors, geometric shapes, or other visual elements that are particularly appealing to the child. This level of customization can be difficult to achieve with humanoid robots, which may have preconceived expectations of how a robot should look or behave.

4 RESEARCH FRAMEWORK AND METHODOLOGY

An elicitation study is a method of determining the preferences and expectations of the general population through collecting data on user-defined actions. The purpose of the study is to test whether the movements of non-anthropomorphic robots can accurately convey emotions. The results of this study may have implications for the development of robots that can accurately convey emotions to users and audiences.

4.1 Participants

Six participants, consisting of three males and three females, took part in the study, including the researchers. All participants were between 18 and 35 years old, had normal or corrected-to-normal vision, and had no known motor or neurological impairments. Participants were informed about the purpose of the study and agreed voluntarily to take part.

4.2 Procedure

Participants were asked to model eight emotions through movement using a Toio robot. The Toio robot was controlled by manually moving it around with the participants' hands. After modelling each emotion, participants were shown a video of the emotions they modelled and asked to answer Likert scale questions about them. The questionnaire included questions about the accuracy of the robot's movement in conveying the emotion and the participant's overall experience and confidence in completing the task. The Toio robot recorded information such as the speed at which it was being moved and the angle it was at during specific time intervals. This information was later used to analyze the accuracy of the movements in conveying emotions.

The experiment took between 15 and 20 minutes for each participant, and all the data collected in this study was kept confidential and used only for research purposes. Participant responses were videotaped.

4.3 Ethics

Participation in this study was entirely voluntary. Participants were free to refuse to participate or to withdraw from the study at any time, without penalty or loss, now or in the future. All data collected in this study were kept confidential and used only for research purposes. If participants had questions about participating in this study, they were encouraged to ask the researchers.

4.4 Implementation

To collect quantitative data, we created a small JavaScript program that measured the x and y positions, along with the angle of the Toio robot every 15ms. From this data, we calculated the metrics in Table 1 and we denote the metrics with their corresponding symbols.

Metric	Symbol	Definition
Average Speed (m/s)	$\overline{s}$	The average speed of the Toio robot
Max Speed (m/s)	$max(s)$	The max speed of the Toio robot
Average Acceleration (m/s^2)	$\overline{a}$	The average acceleration of the Toio robot
Max Acceleration (m/s^2)	$max(a)$	The max acceleration of the Toio robot
Average Angular Velocity (θ/s)	$\overline{\omega}$	The average change in the angular position of the Toio robot
Max Angular Velocity (θ/s)	$max(\omega)$	The max change in angular position of the Toio robot
Variability in Speed (m/s)	Δs	The fluctuation in the speed of the Toio robot
Variability in Angular Velocity (θ/s)	$\Delta\omega$	The fluctuation in the angular velocity of the Toio robot
Total Distance (m)	d	The total distance the Toio robot covers
Total Time (s)	t	The total time of the movement designed

Table 1: Definitions for metrics gathered from Toio robot.

5 RESULTS

During our study, we gathered quantitative data on the position and rotation of the Toio robot. Based on this data, we calculated several key metrics mentioned in Table 1.

5.1 Anger

The analysis shows that anger was strongly associated with high average acceleration, speed, and total distance levels (see fig. 3). However, there was also a significant degree of variability between the maximum and minimum values, indicating that these results were inconsistent across all participants. Anger was usually modelled with sudden fast movements towards the participant/camera, and the motion was described as "shaky", "back and forth", "zig zag", and "attacking". Participants had a high self-reported understanding of anger and were confident in the Toio's ability to convey anger and the clarity of their generated motion, possibly indicating that anger is simple to model using movement (see fig. 4).

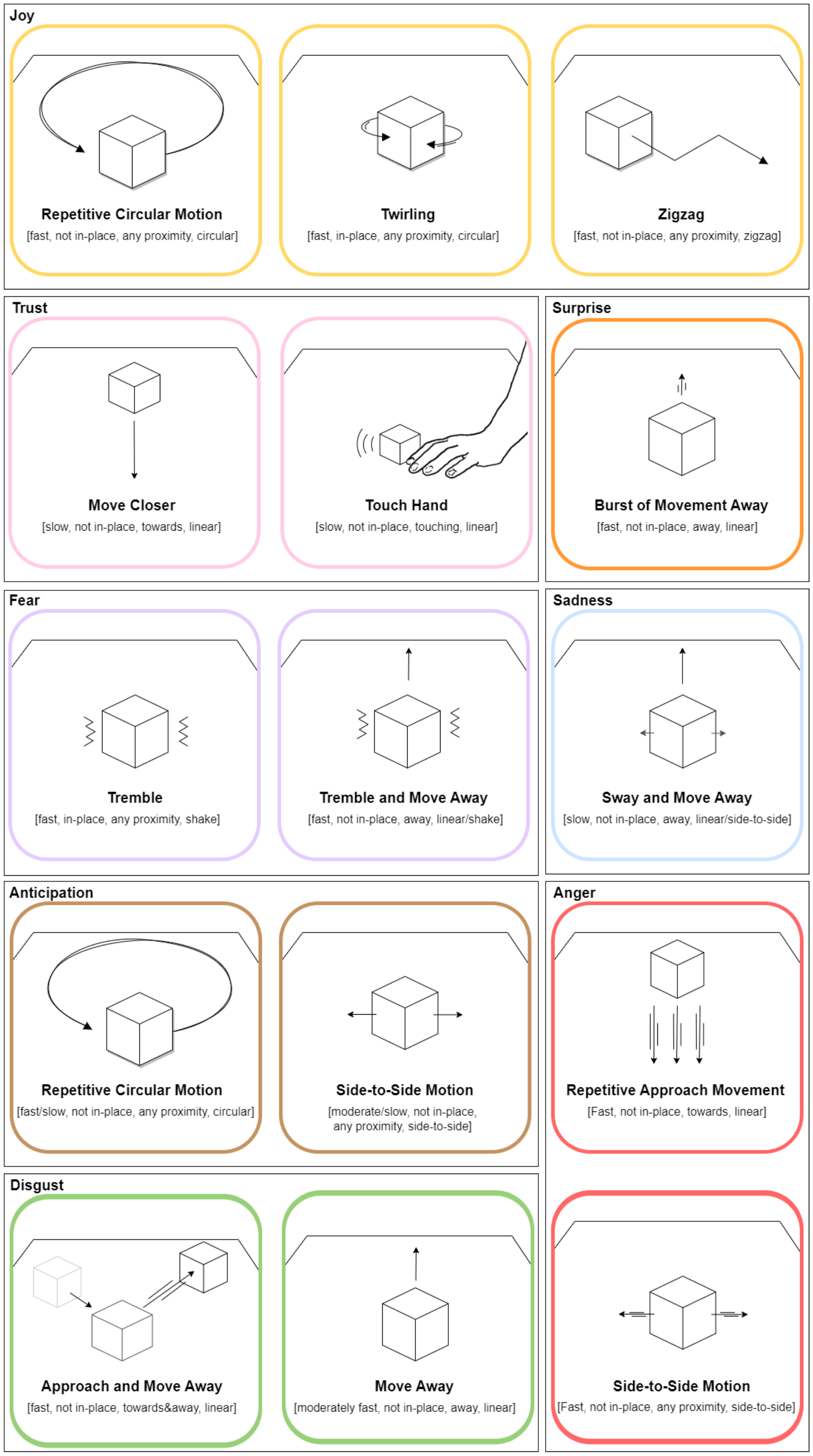

Figure 2: Set of user-defined motions for each emotion. The brackets represent speed, whether the movement is in-place, proximity/direction of movement relative to the user, and the type of motion.

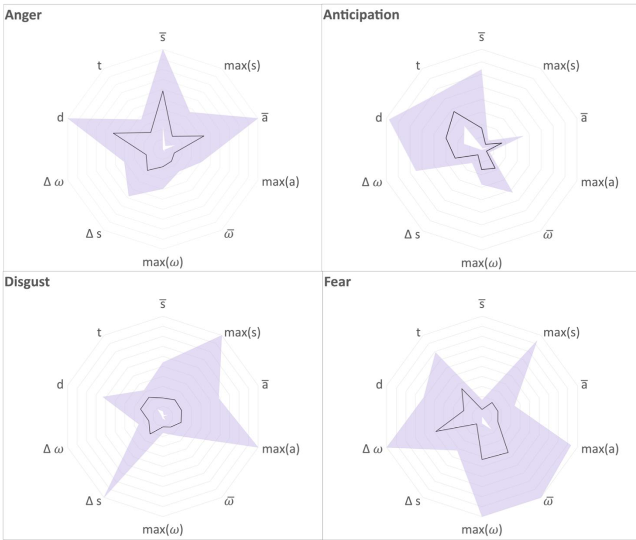

Figure 3: Key metrics for anger, anticipation, disgust, and fear.

Figure 4: Self-reported ratings on participant's understanding of an emotion, confidence in the Toio's ability to model the emotion, and clarity of their motion portrayal of an emotion.

5.2 Anticipation

Overall, the quantitative measurements for anticipation were largely consistent across most participants (see fig. 3). Anticipation was modelled with a back and forth or circular movement, and different participants disagreed on the speed associated with anticipation. Participants lacked confidence in their ability to accurately convey anticipation through their generated movements, and often took more time during the thinking period before finalizing their motion (see fig. 4).

5.3 Disgust

In the study, disgust was typically associated with high maximum speed and acceleration values. Moreover, there was a significant degree of variability in speed when participants modelled disgust (see fig. 3). However, as was the case with anger, there was considerable variation in the results across participants. Disgust was associated with moving away from the participant/camera, with some participants briefly approaching before quickly moving away. Similar to anticipation, participants struggled to model disgust and reported low confidence in their models (see fig. 4).

5.4 Fear

During the study, it was observed that certain participants modelled the Toio robot after the freeze response by causing it to shake. This behaviour led to high average and maximum angular velocity values, accompanied by a high degree of variability in angular velocity (see fig. 3). On the other hand, other participants modelled fear using the flight response, resulting in high values of maximum acceleration and speed for some instances. Participants had a high self-reported understanding, confidence, and clarity of their motion for fear (see fig. 4).

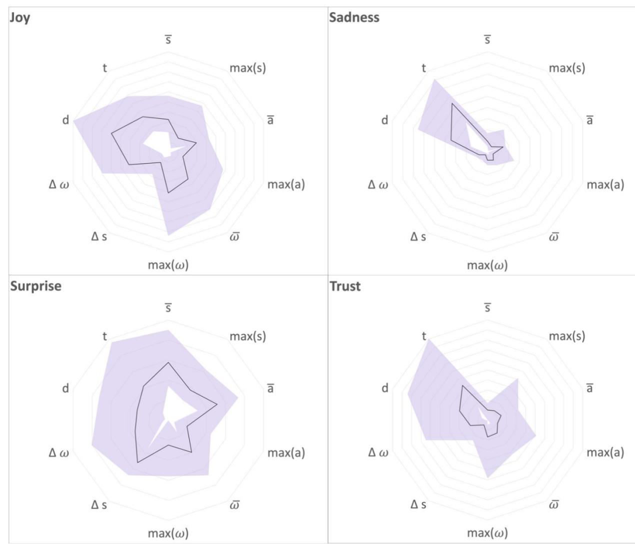

Figure 5: Key metrics for joy, sadness, surprise, and trust.

5.5 Joy

Our analysis revealed that joy was often accompanied by high average and maximum angular velocity values, indicating that participants tended to move the Toio robot in a more dynamic and fluid manner when modelling this emotion. Additionally, it was observed that joy was associated with a large distance covered, suggesting that participants were more active and exploratory in their movements (see fig. 5). Participants described their movement using many dance-related terminology, such as "twirling", "zigzag", or "circular". However, they were only semi-confident in their portrayal of joy (see fig. 4).

5.6 Sadness

In our study, sadness was primarily associated with small values in all movement categories. Notably, there was a high degree of consistency between the results of different participants, indicating that there was a relatively uniform approach to modelling this emotion among the study participants (see fig. 5). Sadness was associated with slow movements, often with a side-to-side sway while moving away from the participant/camera. Participants were relatively confident in their portrayal of sadness (see fig. 4).

5.7 Surprise

Our findings indicate that surprise was typically modelled with a high degree of consistency in terms of variability in speed, with participants often producing similarly fluctuating movements of the Toio robot (see fig. 5). However, there was a notable degree of variability in both total distances covered and time elapsed across different instances of surprise, suggesting that participants approached this emotion with a wider range of movements. Qualitatively, surprise was modelled as quick long or short burst of movement away from the participant/camera described as "jerky" or "side-to-side". Participants were mostly confident in their portrayal of surprise (see fig. 4).

5.8 Trust

Our analysis indicates that the mean and minimum values for trust were generally consistent with each other, suggesting that participants tended to model this emotion with relatively consistent movement patterns (see fig. 5). However, the maximum value for trust was notably larger than both the mean and minimum values, indicating that some participants may have exhibited more extreme or dynamic movements when modelling trust. Participants consistently modelled trust as movement towards the participant/camera, often close to or directly touching the hand. Participants were mostly confident in their portrayal of trust (see fig. 4).

5.9 User-defined Motion set

A user-defined motion set for expressing a specific emotion was created based on movements utilized by at least two participants. Conflict between using the same movement for different emotions were kept, as motions may be interpreted as different emotions depending on the context. For each motion shown in figure 2, the brackets indicate the speed, whether the movement is in-place or not, the direction/proximity of the movement relative to the user, and the type of movement. Respectively, motions for joy, trust, surprise, fear, sadness, anticipation, and anger are represented in yellow, pink, orange, purple, blue, brown, and red boxes respectively.

5.10 General Reflections

To add onto the qualitative results retrieved from participants, most reported that anger was portrayed most effectively in the robot when it was attacking an object such as their hand or a camera. On the other hand, disgust and anticipation were found to be portrayed least effectively, with anticipation being context-dependent and varying in effectiveness depending on whether it was slow or fast. To provide context to the emotions, participants used physical proximity from themselves or the camera. This finding was similar to that of Kim et al., which also found a significant effect [17]. Many of the emotions also shared similar movements, for example circular motion was associated with both joy and anticipation. This suggests that the emotion perceived from a motion can be highly context-dependent. This area of exploration could be further studied in future research. The study also revealed that the Toio robot had very limited emotional expression capabilities, leaving participants wanting more communication modalities such as a head or sound, as well as 3D movements such as jumping for joy and surprise.

6 LIMITATIONS AND FUTURE WORK

While our study provides valuable insights into the ways in which humans model emotions in a simple non-anthropomorphic robot, there are several limitations that suggest avenues for future research. One limitation of our study is the small number of participants which could limit the generalizability of our findings. To address this, a replication study with a larger and more diverse sample size could be conducted to verify the results of our study.

A crucial next step for our research is to investigate the emotional perception of the movements included in our user-generated motion set. Although we were able to observe how participants conveyed specific emotions through their movements, it is essential to examine how these expressions are perceived by others. One such area of work would be the implementation of an interface in which users can model emotions for Toio robots. An example of this would be having users select certain emotions on a sliding scale - perhaps users would like the robot to display an emotion which is composed of 80% anger and 20% sadness.

Another potential direction for future research is to conduct a study with other non-anthropomorphic robots, each with their own unique way of ways of movement capabilities that can express different emotions. Since the robot used in this study was limited to moving in the 2D plane, exploring non-anthropomorphic robots with 3D movement capabilities would be particularly beneficial. Given that earlier research has suggested a correlation between the number of robots present and emotional perception, it would also be valuable to conduct an elicitation study to explore how the movements are emotionally perceived when multiple robots are involved [5, 18]. These studies could help to determine if participants model emotions differently depending on the number of robots and their design and expressive capabilities. Furthermore, an interesting question to explore is whether participants would model emotions differently if they could control the robot's movements remotely, as opposed to manually. This could shed light on how the physical interaction between humans and robots affects their perception and modeling of emotions.

It is also important to note that our study did not account for cultural differences, which could influence the ways in which emotions are perceived and modeled. Thus, conducting cross-cultural studies could be a valuable future direction to further explore these differences.

Overall, by addressing these limitations and exploring these directions, future research can provide a more comprehensive understanding of how humans perceive and model emotions in non-anthropomorphic robots, and how this understanding can be applied in various fields.

7 CONCLUSION

This elicitation study advances our understanding of human perception of emotion conveyed by non-anthropomorphic robots through the analysis of user-defined movements. The study has implications for various fields such as manufacturing and rehabilitation, where robots' emotional expressions can enrich user experiences and improve communication and collaboration with humans. The quantitative analysis of the data reveals specific movement patterns associated with different emotions, but also highlighted the variability in movement patterns among participants. We found that the robot portrayed anger well, but disgust and anticipation were portrayed least effectively. Physical proximity was used to provide context for emotions. Despite some limitations, such as the small sample size, this study lays the foundation for future research in this area, including replication studies with larger and more diverse samples.

Our main contribution in this study is the development of a set of user-defined motions as seen in figure 2. Future work involves validating these user-defined motions with a larger sample size. Furthermore, the implementation an emotion modeling interface for Toio robots where users can select emotions on a sliding scale such as a mix of 80% anger and 20% sadness can be a natural next step from our user-defined set. Overall, this study contributes to the growing body of literature on emotional expression in non-anthropomorphic robots and provides important insights for the design and development of robots that can effectively convey emotions to humans through motion-based expressions.

REFERENCES

[1] Lucy Anderson-Bashan, Benny Megidish, Hadas Erel, Iddo Wald, Andrey Grishko, Guy Hoffman, and Oren Zuckerman. 2018. The Greeting Machine: An Abstract Robotic Object for Opening Encounters. In *2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 595–602. https://doi.org/10.1109/ROMAN.2018.8525516

[2] Lisa Feldman Barrett. 2006. Are Emotions Natural Kinds? *Perspectives on Psychological Science* 1, 1, 28–58.

[3] Mason Bretan, Guy Hoffman, and Gil Weinberg. 2015. Emotionally Expressive Dynamic Physical Behaviors in Robots. *International Journal of Human-Computer Studies* 78 (2015), 1–16.

[4] Paul Bucci, Xi Laura Cang, Anasazi Valair, David Marino, Lucia Tseng, Merel Jung, Jussi Rantala, Oliver S. Schneider, and Karon E. MacLean. 2017. Sketching CuddleBits: Coupled Prototyping of Body and Behaviour for an Affective Robot Pet. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 3681–3692. https://doi.org/10.1145/3025453.3025774

[5] Griffin Dietz, Jane L. E, Peter Washington, Lawrence H. Kim, and Sean Follmer. 2017. Human Perception of Swarm Robot Motion. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI EA '17)*. Association for Computing Machinery, New York, NY, USA, 2520–2527. https://doi.org/10.1145/3027063.3053220

[6] Nem Khan Dim, Chaklam Silpasuwanchai, Sayan Sarcar, and Xiangshi Ren. 2016. Designing Mid-Air TV Gestures for Blind People Using User- and Choice-Based Elicitation Approaches. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (Brisbane, QLD, Australia) *(DIS '16)*. Association for Computing Machinery, New York, NY, USA, 204–214. https://doi.org/10.1145/2901790.2901834

[7] Anca D. Dragan, Kenton C.T. Lee, and Siddhartha S. Srinivasa. 2013. Legibility and predictability of robot motion. In *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 301–308. https://doi.org/10.1109/HRI.2013.6483603

[8] Paul Ekman. 1992. Are there basic emotions? (1992).

[9] Mustafa Suphi Erden. 2013. Emotional Postures for the Humanoid-Robot Nao. *International Journal of Social Robotics* 5 (2013), 441–456.

[10] Ester Ferrari, Ben Robins, and Kerstin Dautenhahn. 2009. Therapeutic and educational objectives in robot assisted play for children with autism. In *RO-MAN 2009 - The 18th IEEE International Symposium on Robot and Human Interactive Communication*. 108–114. https://doi.org/10.1109/ROMAN.2009.5326251

[11] Justin W. Firestone, Rubi Quiñones, and Brittany A. Duncan. 2019. Learning from Users: an Elicitation Study and Taxonomy for Communicating Small Unmanned Aerial System States Through Gestures. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 163–171. https://doi.org/10.1109/HRI.2019.8673010

[12] Kerstin Fischer, Malte Jung, Lars Christian Jensen, and Maria Vanessa aus der Wieschen. 2019. Emotion Expression in HRI – When and Why. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 29–38. https://doi.org/10.1109/HRI.2019.8673078

[13] Márta Gácsi, Anna Kis, Tamás Faragó, Mariusz Janiak, Robert Muszyński, and Ádám Miklósi. 2016. Humans attribute emotions to a robot that shows simple behavioural patterns borrowed from dog behaviour. *Computers in Human Behavior* 59 (2016), 411–419.

[14] John Harris and Ehud Sharlin. 2011. Exploring the Affect of Abstract Motion in Social Human-robot Interaction. In *2011 RO-MAN*. 441–448. https://doi.org/10.1109/ROMAN.2011.6005254

[15] Viviane Herdel, Anastasia Kuzminykh, Andrea Hildebrandt, and Jessica R. Cauchard. 2021. Drone in Love: Emotional Perception of Facial Expressions on Flying Robots *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 716, 20 pages. https://doi.org/10.1145/3411764.3445495

[16] Yuhan Hu and Guy Hoffman. 2019. Using Skin Texture Change to Design Emotion Expression in Social Robots. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 2–10. https://doi.org/10.1109/HRI.2019.8673012

[17] Lawrence H. Kim, Daniel S. Drew, Veronika Domova, and Sean Follmer. 2020. User-Defined Swarm Robot Control. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376814

[18] Lawrence H. Kim and Sean Follmer. 2019. SwarmHaptics: Haptic Display with Swarm Robots. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300918

[19] Heather Knight and Reid Simmons. 2016. Laban head-motions convey robot state: A call for robot body language. In *2016 IEEE International Conference on Robotics and Automation (ICRA)*. 2881–2888. https://doi.org/10.1109/ICRA.2016.7487451

[20] Diana Löffler, Nina Schmidt, and Robert Tscharn. 2018. Multimodal Expression of Artificial Emotion in Social Robots Using Color, Motion and Sound. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Chicago, IL, USA) *(HRI '18)*. Association for Computing Machinery, New York, NY, USA, 334–343. https://doi.org/10.1145/3171221.3171261

[21] Mina Marmpena, Angelica Lim, and Torbjørn S. Dahl. 2018. How does the robot feel? Perception of valence and arousal in emotional body language. *Paladyn, Journal of Behavioral Robotics* 9, 1 (2018), 168–182. https://doi.org/doi:10.1515/pjbr-2018-0012

[22] Christopher Parlitz, Martin Hägele, Peter Klein, Jan Seifert, and Kerstin Dautenhahn. 2008. Care-o-bot 3-rationale for human-robot interaction design. In *Proceedings of 39th International Symposium on Robotics (ISR), Seul, Korea*. Citeseer, 275–280.

[23] Robert. Plutchik. 2001. The Nature of Emotions: Human Emotions Have Deep Evolutionary Roots, a Fact That May Explain Their Complexity and Provide Tools for Clinical Practice.. In *American Scientist*, Vol. 89. JSTOR, 344–350.

[24] María Santos and Magnus Egerstedt. 2021. From Motions to Emotions: Can the Fundamental Emotions be Expressed in a Robot Swarm? *International Journal of Social Robotics* 13 (2021), 751–764.

[25] Ashish Singh and James E. Young. 2012. Animal-Inspired Human-Robot Interaction: A Robotic Tail for Communicating State. In *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction* (Boston, Massachusetts, USA) *(HRI '12)*. Association for Computing Machinery, New York, NY, USA, 237–238. https://doi.org/10.1145/2157689.2157773

[26] Sichao Song and Seiji Yamada. 2017. Expressing Emotions through Color, Sound, and Vibration with an Appearance-Constrained Social Robot. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (Vienna, Austria) *(HRI '17)*. Association for Computing Machinery, New York, NY, USA, 2–11. https://doi.org/10.1145/2909824.3020239

[27] Michael Suguitan and Guy Hoffman. 2018. Blossom: A Tensile Social Robot Design with a Handcrafted Shell. In *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Chicago, IL, USA) *(HRI '18)*. Association for Computing Machinery, New York, NY, USA, 383. https://doi.org/10.1145/3173386.3177539

[28] Santiago Villarreal-Narvaez, Jean Vanderdonckt, Radu-Daniel Vatavu, and Jacob O. Wobbrock. 2020. A Systematic Review of Gesture Elicitation Studies: What Can We Learn from 216 Studies?. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference* (Eindhoven, Netherlands) *(DIS '20)*. Association for Computing Machinery, New York, NY, USA, 855–872. https://doi.org/10.1145/3357236.3395511

[29] Ryan Wistort and Cynthia Breazeal. 2009. TOFU: A Socially Expressive Robot Character for Child Interaction *(IDC '09)*. Association for Computing Machinery, New York, NY, USA, 292–293. https://doi.org/10.1145/1551788.1551862

[30] Satoshi Yagi, Naoki Ise, Shiqi Yu, Yoshihiro Nakata, Yutaka Nakamura, and Hiroshi Ishiguro. 2020. Perception of Emotional Gait-like Motion of Mobile Humanoid Robot Using Vertical Oscillation. In *Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction* (Cambridge, United Kingdom) *(HRI '20)*. Association for Computing Machinery, New York, NY, USA, 529–531. https://doi.org/10.1145/3371382.3378319

[31] Ran Zhou, Harpreet Sareen, Yufei Zhang, and Daniel Leithinger. 2022. EmotiTactor: Exploring How Designers Approach Emotional Robotic Touch. In *Designing Interactive Systems Conference* (Virtual Event, Australia) *(DIS '22)*. Association for Computing Machinery, New York, NY, USA, 1330–1344. https://doi.org/10.1145/3532106.3533487

[32] Xiaoyan Zhou, Adam S. Williams, and Francisco R. Ortega. 2022. Towards Establishing Consistent Proposal Binning Methods for Unimodal and Multimodal Interaction Elicitation Studies. In *Human-Computer Interaction. Theoretical Approaches and Design Methods*, Masaaki Kurosu (Ed.). Springer International Publishing, Cham, 356–368.

[33] Álvaro Castro-González, Henny Admoni, and Brian Scassellati. 2016. Effects of form and motion on judgments of social robots' animacy, likability, trustworthiness and unpleasantness. *International Journal of Human-Computer Studies* 90 (2016), 27–38. https://doi.org/10.1016/j.ijhcs.2016.02.004