Emotive Response to a Hybrid-Face Robot and Translation to Consumer Social Robots

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***Abstract*—We present the conceptual formulation, design, fabrication, control, and commercial translation of an Internet of Things (IoT)-enabled social robot as mapped through validation of human emotional response to its affective interactions. The robot design centers on a humanoid hybrid face that integrates a rigid faceplate with a digital display to simplify conveyance of complex facial movements while providing the impression of 3-D depth. We map the emotions of the robot to specific facial feature parameters, characterize recognisability of archetypical facial expressions, and introduce pupil dilation as an additional degree of freedom for emotion conveyance. Human interaction experiments demonstrate the ability to effectively convey emotion from the hybrid-robot face to humans. Conveyance is quantified by studying neurophysiological electroencephalography (EEG) response to perceived emotional information as well as through qualitative interviews. The results demonstrate core hybrid-face robotic expressions can be discriminated by humans (80%+ recognition) and invoke face-sensitive neurophysiological event-related potentials, such as N170 and vertex positive potentials in EEG. The hybrid-face robot concept has been modified, implemented, and released in the commercial IoT robotic platform Miko ("My Companion"), an affective robot currently in use for human–robot interaction with children. We demonstrate that human EEG responses to Miko emotions are comparative to that of the hybrid-face robot validating design modifications implemented for large-scale distribution. Finally, interviews show above 90% expression recognition rates in our commercial robot. We conclude that simplified hybrid-face abstraction conveys emotions effectively and enhances human–robot interaction.**

***Index Terms*—Affective robot, brain–robot interface, emotional response, event-related potential (ERP), facial expression, human–robot interaction.**

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I. INTRODUCTION

AFFECTIVE social robots are gaining increasing interest in research and social applications. However, achieving smooth human–robot interaction still has significant challenges such as making robots trustworthy through the incorporation of emotional compatibility in their interactions [1]–[4]. Humanoid social robots provide means to investigate social cognition, engage with, and support human mental health. Humans respond better to robots that behave empathetically toward them, by recognizing emotion and responding accordingly [5]–[11]. The fundamental work by Brazeal and Ishiguro [4], [12]–[14] grounded this field of affective human–robot communication (see [7], [8], [15], [16] for recent surveys). Industry translation of social robots has also begun in service and hospitality sectors, though challenges in reliability and acceptance by humans remain unresolved [17]. In this study, we develop a practical approach to design simplified affective robots to convey emotions effectively.

For a successful natural human–robot collaboration, social robots must adopt a multimodal approach with capability to show facial expressions, speech, gestures, access online knowledge, understand context and intent, be aware of surroundings, and adapt their behavior accordingly. This can be achieved by connecting social robots to the Internet of Things (IoT) and cloud services to enhance their social and emotional capabilities [18]–[20] while improving security [21]. IoT-based social robots have been proposed for use in education [22], special needs [23], in healthcare for cognitive therapy [24], and assistive and care services [19], [21], [25], all of which require an emotional connection, empathy, and trust with users. There has been relatively less research on embedding sensory information from IoT to develop interactive social robots for detecting and responding to emotions using facial expressions.

Ekman [26] proposed that all human expressions can be represented by a combination of six basic universal expressions: 1) happy; 2) sad; 3) angry; 4) afraid; 5) surprise; and 6) disgust, according to the facial action coding system (FACS) [27]. Thus, emotions can be characterized by using continuous scales or by a 3-D "affect space" with arousal, valence, and stance axes, building upon which we propose two emotion representation models in this study. Facial configuration is also important for emotion recognition. The design of social robots must avoid the "uncanny valley" [28] causing negative emotional response in humans if robots appear eerily human like.

The development and maintenance of fully actuated expressive robotic faces require complex mechatronic design and control [29], which despite many successful applications are a limiting factor for widespread adoption and commercial use. Fully actuated robot faces are less flexible to adapt new expressions or to make them culturally sensitive [30] as they have fixed limited Degrees of Freedom (DoF) to convey expressions. Integrating features such as pupil dilation, which are integral for human-like emotive conveyance in actuated robot faces, is challenging [31]. This has motivated a significant research, including our own work, aimed at simplification of emotive robot faces for cost and ease of use (e.g., [32]–[35]).

Finally, while human–robot affective communication is a maturing field, the empirical assessment of human–robot affective interactions has not been fully addressed. Recent investigations using FACS [34] show potential for empirical assessment; however, there is a paucity of research in assessing conscious and subconscious human emotional response to the robot's facial expressions as compared to affective interaction with virtual avatars [15]. The direct analysis of human physiological response to robot expressions using brain imaging (e.g., [35]) or electroencephalography (EEG) has a significant potential to quantitatively asses human–robot interactions and engagement.

Processing emotions and facial expressions involves several task-specific neuron sources [36] from different parts of the brain [37], especially from the right hemisphere [38], [39]. A common method of assessing neurophysiological response in EEG is by studying event-related potentials (ERPs), which are positive or negative voltage deflections time locked to stimulus onset [40]. N170 and vertex positive potentials (VPPs) are well-documented face-sensitive ERP components [41]–[43] that are evoked preferentially, but not exclusively in response to faces [43], [44]. N170 is a negative potential observed in the occipito-temporal region, while VPP is a corresponding positive potential observed simultaneously in the central region, with latency of around 170 ms in response to visual face stimulus [45]. N170 and VPP are two corresponding manifestations of the same brain processes, occurring at same time, and showing identical functional properties [45]. N170 is observed in face-sensitive structural encoding stage occurring before the recognition of face and is unaffected by emotional content within expressions [39], [46]; however, some studies have shown modulations in N170 by emotional faces [47], [48]. Hence, we present ERP study of N170 and VPP for empirical quantification of human visual response to a robot's face [49].

We thus identify the following gaps in the research of affective social robots and their interaction with humans and requirements for commercial translation of social robots.

1) The demand for social robots for daily use necessitates practical approaches to the design of affective platforms that may function in uncontrolled environments. Conveyance of emotive expression through canonical abstraction of robotic facial features can balance meaningful human–robot interaction with robustness, utility, and computational cost [50], [51].
2) Fully actuated robotic faces are less viable for consumer use due to challenges and expense in fabrication, maintenance, and adaptability. Robot faces using high-resolution realistic digital graphics are robust and flexible, yet complex to program, require higher computational power, and can be off-putting. There is a need to create pragmatic models for social robots that can be realistically translated for widespread use whilst preserving aspects of actuated robot faces (e.g., 3-D features) combined with flexibility and adaptability of simple digital graphics [30].
3) Social robots with the capacity to incorporate cognitive, affective, and speech demands robotic integration into IoT platforms for contextual awareness. This enables adaptive interaction and advanced functionality through communication with smart environments [18]–[20]. Social robots need pervasive connection to cloud databases and other smart objects to adjust behavior to human beings [52]. Establishing this is critical for consumer use in the home.
4) Pupil dilation is vital in human affective communication and, despite potential to enhance robot emotions [31], [53], yet remains largely unexplored in digital robots.
5) Literature lacks quantitative methods to empirically assess human–robot affective interaction. The quantification of neurophysiological response of humans to robotic emotions also remains underexplored.
6) There is paucity of research studies to draw from illustrating the complete life cycle from conceptualization, robot design, human testing, and translation to consumer deployment.

In this study, we introduce a complete hybrid-face affective robotic system to convey human-like facial emotions without the complexity of full facial actuation and demonstrate its translation to commercial IoT robot ("Miko"—my companion) that is in use today for affective robot interaction with children. This provides a basis for the larger goal of developing mechanically simple platforms for human–robot engagement as well as a method to quantify, physiologically, human response to affective robots. The aims of this study are as follows.

1) Develop a practical method to design a simplified hybrid-face affective robot capable of emotive conveyance and propose affect space representations for emotions.

2) Empirically validate human–robot affective interaction with our platform using behavioral (conscious) response and neurophysiological ERP N170/VPP (subconscious) response.
3) Implement these methods to develop, validate, and translate the hybrid-face robot concept from research platform to a mass-market IoT social robot (“Miko”). Using these findings, deploy the platform for widespread use.
4) Validate behavioral and neurophysiological responses to the mass market Miko platform through demonstration of parallel human responses to the research platform; illustrate the efficacy of the hybrid-face robot concept and its modifications for widespread accessibility, answering: How effective are these robots in conveying emotions?

II. Hybrid-Face Affective Robot

A. Design of Hybrid-Face Affective Robot

The hybrid-face robot shown in Fig. 1(a) combines a digital face with a static 3-D printed human visage-like structure [Fig. 1(b)]. It is designed to provide the flexibility of a digital countenance with some of the benefits of a fully actuated face.

The hybrid-face robot consists of eyebrows, eyelids, eyeballs, and mouth, with a total of thirteen DoF [Fig. 1(d)]. These 13 values characterize the facial expression at any given time. The hybrid face was programmed in the OpenGL environment and rendered using Face3-D.

We propose two types of affect space representations to generate emotions for the hybrid-face robot—*categorical affect space* and *3-D affect space*, described below. We also added eye blinks, subtle twitching, and constant motion of eyes to make the hybrid-face robot more dynamic, expressive, realistic, and likeable. Further details of the hybrid-face robot affect space design summarized below are given in our previous work [51].

1) Categorical Affect Space Emotion Representation: The categorical affect space represents the robot’s facial expression by a linear combination of its basis expressions. Our set of basis expressions, extended from Breazeal’s work [54], consists of *happy, sad, angry, afraid, surprise, tired, stern*, and *disgust* ($B = \{\vec{b}_1, \vec{b}_2, \ldots, \vec{b}_n\}$), each of which is a vector containing 13 values corresponding to 13 DoF of a hybrid-face.

An expression $\vec{e}$, is created by a weighted linear combination of variances of different expressions from neutral expression ($\vec{b}_i - \vec{b}_N$) added to the neutral expression $\vec{b}_N$

$$\vec{e} = \left(\sum_{i=1}^{n}\left(\vec{b}_i - \vec{b}_N\right)\vec{w}_i\right) + \vec{b}_N$$

where n is a number of basis expressions, and the weight vector with a weight corresponding to each basis expression is $\vec{w} = [w_1,\ w_2, \ldots,\ w_n], w_i \in [0,\ 1]$. Fitzpatrick *et al.* [55] and Bruce *et al.* [56] have shown that such emotions can be used in sophisticated human–robot interactions. The categorical affect space model is generalizable to accommodate any number of basis expressions, although we use eight basis expressions in this study.

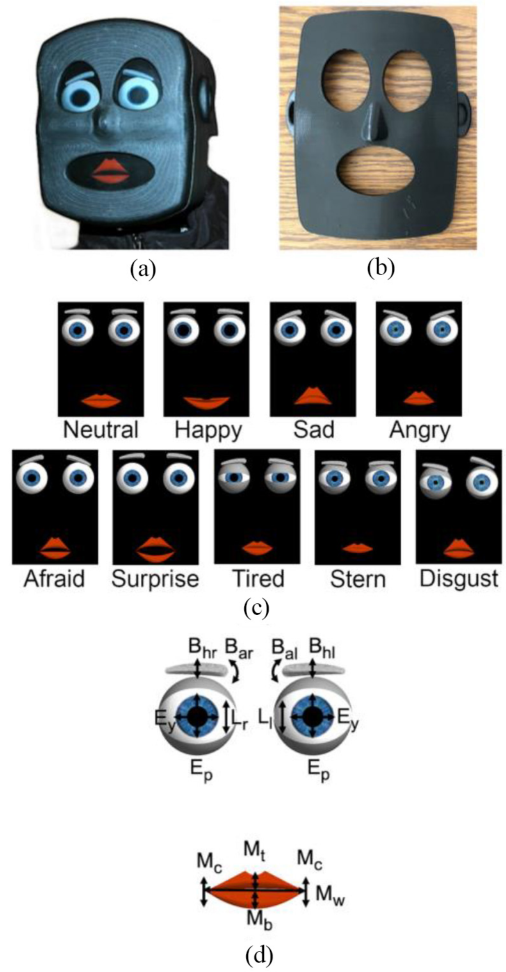

Fig. 1. Hybrid-facer robot and its facial expressions. (a) Hybrid-face robot with a faceplate and digital display. (b) 3-D printed faceplate. (c) Facial expressions of the hybrid-face robot. (d) Hybrid-face robot’s 13 DoF: left and right eyebrow angle B_{al} and B_{ar}; left and right eyebrow vertical height B_{hl} and B_{hr}; left and right eyelid openness L_l and L_r; eye pitch and yaw E_p and E_y; pupil size P; mouth corner vertical height M_h; mouth width M_w; top lip openness M_t; and bottom lip openness M_b for emotion depiction.

2) 3-D Affect Space Emotion Representation: We developed a 3-D affect space for the hybrid-face robot inspired by Breazeal [54]. Unlike typical 2-D affect space with *arousal* and *valence* axes [57], [58], we use three dimensions with *arousal*, *valance*, and *stance* axes (Fig. 2), capable of capturing the vast majority of facial expressions [57], [59]. This 3-D affect space model is based on six basis expressions unlike categorical model which can use any number of basis expressions. The three axes are characterised by six basis expressions $B = \{\vec{b}_{\text{happy}}, \vec{b}_{\text{sad}}, \vec{b}_{\text{surprise}}, \vec{b}_{\text{tired}}, \vec{b}_{\text{angry}}, \vec{b}_{\text{afraid}}\}$, with pairs of opposite expressions on each end of axis: valence axis with happy and sad, arousal axis with surprise and tired, and stance axis with angry and afraid. Each expression is a linear combination of three basis expressions, one on each of the axes.

The representation of an expression $\vec{e}$ at a location $\vec{x} = [\alpha\ \beta\ \tilde{a}]^T,\ \alpha,\ \beta,\ \gamma \in [-1,\ +1]$ in the 3-D affect space is given by the linear combination of variances of basis expressions along three axes from neutral expression ($\vec{b}_i - \vec{b}_N$)

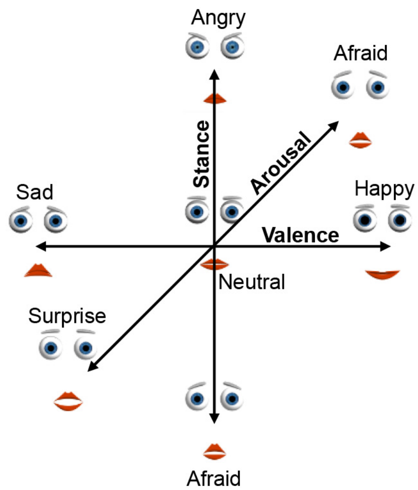

Fig. 2. Three-dimensional affect space represented by axes of arousal (high or low), valence (positive or negative), and stance (open or closed).

as follows:

$$\begin{aligned}\vec{e} &= \max(\alpha,\ 0)\left(\vec{b}_{\text{happy}} - \vec{b}_N\right) + \max(-\alpha,\ 0)\left(\vec{b}_{\text{sad}} - \vec{b}_N\right)\\ &\quad + \max(\beta,\ 0)\left(\vec{b}_{\text{surprise}} - \vec{b}_N\right) + \max(-\beta,\ 0)\left(\vec{b}_{\text{tired}} - \vec{b}_N\right)\\ &\quad + \max(\gamma, 0)\left(\vec{b}_{\text{angry}} - \vec{b}_N\right) + \max(-\gamma, 0)\left(\vec{b}_{\text{afraid}} - \vec{b}_N\right) + \vec{b}_N\end{aligned}$$

where the maximum function max negates the contribution of a basis expression if $\vec{x}$ is closer to its opposite basis expression.

Our implementation draws from Breazeal's choice of stance to alleviate discrimination by separating fear from anger, giving both a slightly negative valence and high arousal. We chose to simplify the model by characterizing stance axis by anger (in the positive direction) and fear (in the negative direction) to reduce the set of bases for affect space and decrease computational expense. Also, expressions cannot show anger and fear at the same time; hence, we gave both a role of basis expressions. Open and closed/stern stances can be expressed by a combination of arousal, valence, and stance, when stance is characterized by the fear and anger expressions. Given the eventual goal of translation, some modifications were based on subjective assessment of expected use and ability to run on simple platforms in conjunction with embedded systems.

B. Participants

To assess conscious and subconscious responses to the hybrid-face robot, we performed tests with 19 healthy participants (22–58 years, 9 female, and 10 male). This group of participants was selected from a wide age range and diverse professions to better resemble the population that social robots would have to engage with. All 19 participants participated in behavioral response experiments out of which 12 also took part in neurophysiological experiments. Ethical approval for the study was obtained from the University of Bristol Ethics Committee and all participants gave informed written consent.

C. Behavioral Response to Hybrid-Face Robot

1) Emotion Recognition Experiment: A forced-choice expression recognition task [12], [60], [61] was conducted for qualitative assessment of recognition of the hybrid-face robot emotions. Participants were seated in front of a hybrid-face robot and shown different robot expressions (happy, sad, angry, afraid, surprise, tired, stern, and disgust) in a random order. Each expression was displayed on the hybrid-face robot for 4 s each after which participants were asked to select the best matching emotion from a provided list of above eight emotions. Several instances of each expression were repeated with different combinations of static expression, expression with realism features (blinks and twitches), and expression with animation that smoothly transitioned from neutral expression.

2) Pupil Dilation Experiment: Pupil dilation occurs in humans in response to different emotional states [62], increased attention and engagement [63], and faces with dilated pupils that are also perceived as more attractive [64]. Hence, in this experiment, we wanted to assess whether including pupil dilation in the robot face can depict different emotional states more effectively. We aimed to quantify correct empirical values of pupil dilation that match different robot expressions better. Identifying correct pupil dilation values that humans may innately associate with a "universal standard" for different expressions could improve emotion recognition rates for robot emotions.

Participants were seated 1 m away from the robot. Each of the eight robot facial expressions was shown with a minimal pupil dilation size of 10-mm diameter that increased gradually to a maximum size of 40-mm diameter at the rate of 0.6 mm/s, on a white sclera of 85 mm diameter surrounding a blue iris with a 45-mm diameter. During these gradual transitions of pupil dilation from minimum to maximum for each expression, participants were asked to report three pupil dilation values: 1) when they felt that the pupil dilation began to suit the face (this was recorded as the minimum value); 2) when the pupil dilation matches the presented expression (this was recorded as the target value); and 3) when pupil dilation begins to mismatch with the facial expression (this was recorded as the maximum value of pupil dilation). The minimum, maximum, and target pupil dilation values for each robot expression as subjectively reported by participants were then compared.

D. Neurophysiological Response to Hybrid-Face Robot

Drawing from physiological studies on the quantification of neural response to face stimulus, EEG experiments were conducted to study the subconscious response of humans to robot affective faces. The purpose was to investigate if robotic emotion conveyance could evoke predominantly face-sensitive N170/VPP ERP neurological response. To validate our ERP experimental paradigm and provide a baseline with N170 response evoked by human faces, we conducted a prepilot with a subset of three participants (see Appendix A). Participants were shown pictures of human faces from Japanese Female Facial Expression database [65] with

Fig. 3. EEG experiment setup with the participant seated in front of hybrid-face robot and monitor.

different standardized emotions as per FACS on a monitor and EEG was recorded.

1) Experimental Design: Participants seated 1 m away from a monitor and hybrid-face robot (Fig. 3) were naïve to the research question and were asked to simply observe robot expressions. Neurophysiological response to structured robot facial expressions shown in Fig. 1(c) and the effect of faceplate on robot emotion presentation with context (on hybrid-face robot with 3-D faceplate) or without context (same digital robot face on monitor without 3-D faceplate) was studied. Eight basic robot expressions along with neutral expression presented on monitor and hybrid-face robot were generated using categorical affect space emotion representation described in Section II-A1. For the experiment with the digital robot face on a monitor, a fixation cross was presented for a random duration around 2 s followed by a robot emotion in random order for 1 s. A blank screen was displayed for 1 s between trials. The experiment with hybrid-face robot followed the same structure, and only the robot emotion was presented on the hybrid-face robot, which provided additional configurational information such as 3-D facial structure with ears, cheeks, and nose. 25 EEG trials were recorded for each emotion for robot and monitor conditions.

2) EEG Recording: EEG was recorded using a 16 channel 24 bit g.tec USBAmp (g.tech medical engineering, Schiedlberg, Austria), sampled at 256 Hz with online bandpass-filtering between 0.1 and 30 Hz. Electrodes were placed at Fp1, Fpz, Fp2, F3, Fz, and F4 (frontal), C3, Cz, and C4 (central), T7 and T8 (temporal), P7, P3, Pz, P4 and P8 (parietal), and Oz (occipital) locations according to the 10-20 international system with reference at left ear lobe and ground at Fpz. Electrode impedance was kept below 20 kΩ.

3) ERP Analysis: EEG recorded while user was shown different robotic expressions on hybrid-face robot and on monitor was first filtered between 0.1 and 20 Hz using a zero-phase shift digital low pass filter. Artefacts were removed by rejecting EEG trials with amplitude greater than $\pm 70\ \mu$V on channels Fp1 and Fp2 and by visual inspection. The artefacts removed EEG was segmented into epochs of -100 to 400 ms after the stimulus onset (display of robotic expression). The grand average ERP was extracted by averaging these time locked trials across subjects and each robotic expression forms the two sources hybrid-face robot and monitor. We characterized the latency of N170 ERP component by averaging percentiles from minimum amplitude within 130–190 ms poststimulus time window.

TABLE I
CONFUSION MATRIX OF OVERALL EMOTION RECOGNITION ACCURACIES (%) FOR HYBRID-FACE ROBOT

	Happy	Sad	Angry	Afraid	Surprise	Tired	Stern	Disgust
Happy	84.8	1.3	2.7	1.3	4.6	4.0	1.3	0
Sad	1.5	88.8	0.6	3.9	1.3	0.6	2.0	1.3
Angry	3.3	2.7	68.5	3.3	0.6	0.6	21.0	0
Afraid	2.0	28.2	2.6	50.0	9.9	3.3	2.0	2.0
Surprise	2.7	2.0	1.3	9.2	79.6	3.2	2.0	0
Tired	0	3.2	6.6	4.0	2.0	69.0	14.5	0.7
Stern	0	6.0	10.7	0.7	4.0	14.0	59.2	5.4
Disgust	4.6	4.6	0	0	15.8	6.6	4.6	63.8

TABLE II
EMOTION RECOGNITION ACCURACIES (%) FOR HYBRID-FACE ROBOT IN STATIC, ANIMATION, (TRANSITIONING FROM NEUTRAL EXPRESSION) AND REALISM (BLINKS AND TWITCHES) CONDITIONS

	Happy	Sad	Angry	Afraid	Surprise	Tired	Stern	Disgust
Overall	84.8	88.2	68.5	50.0	79.6	69.0	59.2	63.8
Static	89.5	89.5	76.3	50.0	84.2	76.3	51.2	65.8
Animation	79.0	81.6	55.3	44.8	86.8	63.2	57.9	57.9
Realism	86.9	89.5	71.0	55.3	84.2	71.1	65.8	68.4
Animation & Realism	84.2	92.1	71.0	50.0	63.1	65.81	60.5	63.2

E. Results of Hybrid-Face Robot Experiments

1) Behavioral Response to the Hybrid-Face Robot: Table I shows the confusion matrix of average emotion recognition accuracies from forced-choice experiments under all conditions (static, realism, animation, and their combination). Happy, sad, and surprise expressions had the highest recognition accuracies. However, stern was confused with tired and angry, angry was confused with stern, afraid was confused with sad, and disgust was confused with surprise, possibly due to the similarity between the expression features. Poor identification of emotion disgust is well noted in [24]–[26]; however, we observed lowest accuracies for afraid and stern with the hybrid-face robot.

Table II shows correct emotion recognition percentages under animation implemented by showing smooth transition to the target expression from neutral expression over 2 s, realism with blinks and twitches and static conditions. Even though most participants mentioned they preferred the animation showing transition of emotion from neutral expression, there was decrease in recognition rates for angry, afraid, tired, and disgusted. This is also in contrast with the literature that states animating facial expressions through transition stages should increase success rate of recognition [66]. This decrease in recognition could be due to unnatural speed of animations highlighted in some studies that can lead to uncanny valley effect [28], [67]. Further study is necessary in this arena.

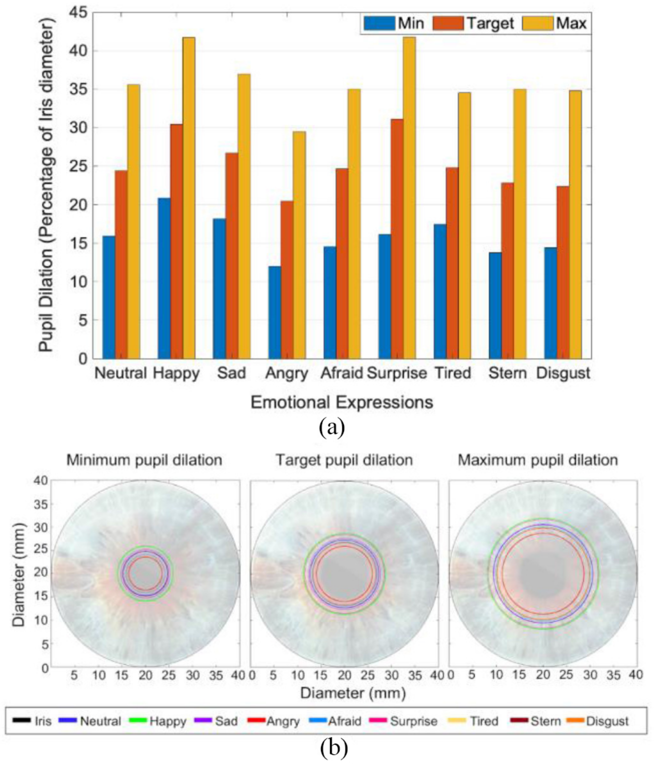

Fig. 4. Pupil dilation results. (a) Grand-average results for pupil dilation expectations to match emotion for three interest points: minimum, target, and maximum presented as percentage of the total iris size. (b) Grand-average results for pupil dilation to match emotion for three interest points illustrated on the image of iris for comparison.

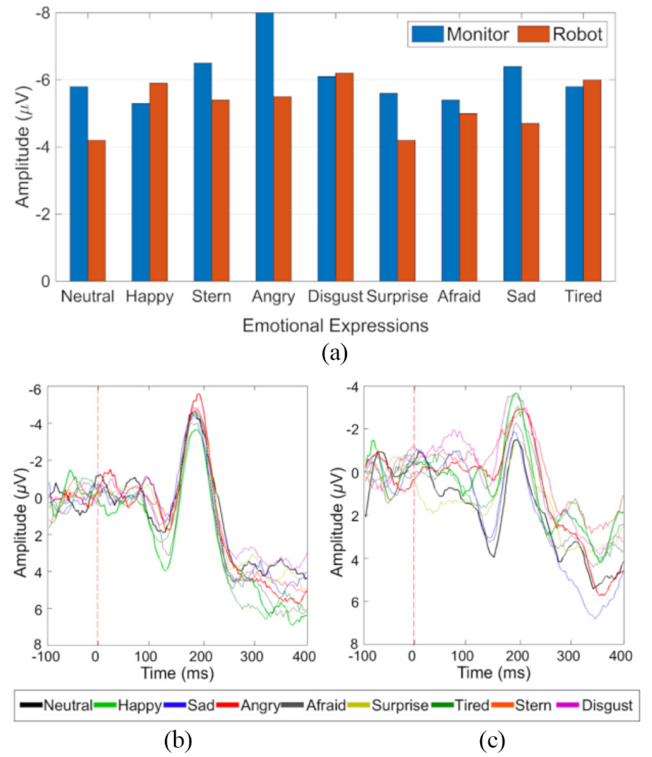

Fig. 5. N170 ERP response to hybrid-face robot expressions. (a) Comparison of N170 ERP amplitudes between stimulus sources (monitor and hybrid-face robot) for all emotions at P8. (b) Grand-averaged ERP waveforms for digital expressions presented on the monitor (without context) at P8. (c) Grand-averaged ERP waveforms for digital expressions presented on the hybrid-face robot (with context) at P8.

2) Effect of Pupil Dilation on Emotion Recognition: The results for pupil dilation experiment, recorded as the percentage of iris diameter, are presented in Fig. 4(a). The pupil dilation for a given expression was recorded for three interest points: 1) minimum; 2) target; and 3) maximum pupil dilation.

The pupil dilation for the happy expression is consistently greater than neutral expression across the three interest points. Surprise is the only other emotion to provide an equally large dilation percentage comparable with happy. Angry has consistently the smallest pupil size across all interest points. The ideal target size of pupil dilation for the neutral expression was consistent at 25% of the iris diameter.

Results indicate the difference between expected pupil dilation for emotional face diagrams as a percentage of total iris diameter relative to neutral, and the relationships can be suggested; happy (+3 to +8%), stern (−2%), angry (−3 to −5%), afraid (−3%), sad (+4%), and disgust (+1 to +3%). The results for tired vary inconsistently across interest points. Results for the three interest points suggesting these relationships are presented as percentages of the total iris size to allow for comparison and across emotions [Fig. 4(b)].

The results across the three interest points for other emotions vary around neutral and between happy and angry expressions. While small differences between grand-average results for each emotion can be due to with-in variation, an overall relationship between pupil dilation and the happy, angry, and neutral face diagrams is demonstrated.

3) Physiological ERP Response to the Hybrid-Face Robot: A clear face-sensitive N170 ERP was observed in the occipito-temporal region for hybrid-face robot emotions. The grand-average N170 ERP amplitudes and waveforms are presented in Fig. 5 for each emotion at P8, for both robot and screen sources. This ERP response was similar to N170 ERP response to pictures of human facial expressions as described in Fig. 9 in Appendix A.

The statistical significance of different expressions and effect of context presentation on ERP was assessed using analysis of variance (ANOVA). Facial expressions with strong positive or negative emotions evoked a larger ERP response than neutral. Angry emotion showed highest amplitude $\text{Angry}_{\text{MONITOR}}$ ($F(1, 259) = 3.03$, $p = 0.083$) and $\text{Angry}_{\text{ROBOT}}$ ($F(1, 259) = 4.43$, $p = 0.036$). The differences in the amplitude and latencies of N170 for different emotions within the same stimuli presentation source (monitor or robot) were not statistically significant. However, differences in amplitude of N170 between the two stimuli presentation sources were statistically significant ($F(1, 17) = 11.73$ $p<0.01$). The topography of EEG showing ERP responses in the two stimuli presentation sources for different emotions is shown in Appendix B. Negative potential N170 was observed in occipito-temporal region and its corresponding positive potential (VPP) was simultaneously observed in the central region (Fig. 10 in Appendix B). N170 from hybrid-face robot was observed with an average delay of 7 ms as compared to digital face on monitor (Fig. 5). Delay in N170 latency and suppression of amplitude were also observed in 3-D hybrid-face robot as compared to robot's digital face on monitor and human face pictures (Fig. 9 in Appendix A).

III. Translation of Hybrid-Face System for Mass-Market Social Robot

The hybrid-face robot concept has been validated for its capacity to convey different emotions successfully as shown by the qualitative assessment with strong recognition rates by humans and by quantitative assessment of face-sensitive N170/VPP ERP neurophysiological responses. These results provide a basis for full translation of the hybrid-face concept in the development of a commercial social robotic platform. The next sections detail the development and testing of an application of hybrid- face robot in a IoT social robot Miko (Mumbai, India). Despite its simplicity, a full hybrid-face robot with all 3-D facial features was not practical as a stand-alone device for mass market. A further simplified version of the face and expressions was necessary that would appeal to target users, in this case children without compromising recognition rates and human response to emotions, while improving likeability. Miko was developed iteratively in two subsequent versions that incorporated more facial features of hybrid-face robot.

A. Design of Miko Social Robot

Miko robot is an intelligent IoT-based social robot designed for educational purposes (https://miko.ai/in). Miko draws upon the hybrid-face robot concept to improve the human–robot affective interaction. The first-generation robot we have produced, Miko I, is simplified from the original hybrid-face robot and consists of eyes which can show different emotions to facilitate communication. The hybrid face of Miko I itself is placed on its head, which also has ears and a curved surface, giving an illusion of depth (Fig. 6). Design choices, such as the curved hybrid-face, color, ears, and shape were chosen through qualitative experiments with customers and tools such as quality functional deployment (QFD). The development of Miko I was guided by a user centric design approach involving feedback from over 300 young school students. Students were able to identify majority of the Miko expressions and always correctly identified whether the emotion associated to the displayed expression was positive or negative. Sound cues helped identification of emotions; however, a clear visual representation of expression was found to be more important. Communication with Miko I occurs through IoT connectivity via an app that allows users to talk and send various emotions using different emoticons. Miko I displays received emotions along with audio and light stimuli as well as small movements matching the emotions. The range of emotions for Miko I, drawing from the hybrid face, is shown in Fig. 6.

In this study, we focus on the recognition and neurophysiological response of emotions displayed on the hybrid-face of Miko I to validate its capacity to evoke human emotive

Fig. 6. Miko I social robot with a curved display resembling a 3-D structure of a face showing different emotions.

response. Having established a procedure for response validation, we execute this procedure with Miko I and compare its response to that of the full hybrid-face robot with 13 DoF.

The depiction of emotions of Miko I is simplified using eyes only and do not show the gradation/transition depending on parameters as with the full hybrid-face robot. Facial design of Miko I is inspired by and is an abstraction of hybrid-face robot. This design choice was made to appeal younger users as it resembles emoticons that children are familiar with, with an assumption that it will lead to greater engagement with the robot. The hybrid-face graphics were designed by researchers inhouse to test the proof of concept. Building upon hybrid-face robot, facial graphics were redesigned by professional designers to suit the body and color scheme of Miko I to improve its visual appeal for commercialization by keeping the core concept of robot same. We found that N170 ERP response to robot emotion presentation without faceplate was significantly higher ($p<0.01$) than with faceplate (see Section II-E3), but pragmatically depth was useful and more appealing in a humanoid robot; hence, we adopted curved face and ears in Miko while eliminating the faceplate. While more complex facial features from hybrid-face robot were incorporated in the next release as detailed in Section III-F, we wish to test if the simplified emotions in Miko I provide comparable conveyance and recognition via behavior and neurophysiological (N170/VPP ERP) studies. This will help us answer another key question—what are minimum facial features of a social robot or maximum level of abstraction that give equal neurophysiological response and recognition rates as fully featured hybrid-face robot?

B. Participants

To assess conscious and subconscious responses to Miko I robot similar to hybrid-face robot, we performed tests with two groups of healthy participants. A group of 15 participants (19–29 years, 5 female, and 10 male) participated in the behavior response experiments with Miko I and a second group of ten participants (22–29 years, 1 female, and 9 male) participated in the neurophysiological response experiments. The ethical approval for the study was obtained from Imperial College

London Science, Engineering and Technology Research Ethics Committee and all participants gave informed written consent.

C. Behavioral Response to Miko I Robot

We repeated the behavioral analysis with emotion recognition task on Miko to qualitatively assess recognition of different expressions shown by Miko. The experiment structure was the same as the forced-choice experiment conducted with the hybrid-face robot described in Section II-C1. To avoid response bias, subjects who had never interacted with robot Miko were selected. Participants were given a list of the same emotions and after each emotion shown by Miko, they were asked to select the best matching emotion. Emotions were sent to Miko manually from its companion mobile app and each emotion was displayed for 4 s with several repetitions in random order. In this experiment, the movement of Miko was constricted but the sound and light stimulus occurring along with the facial expressions were kept on, which might help in emotion recognition. The recognition rate of different Miko expressions was recorded.

D. Neurophysiological Response to Miko I Robot

The aim of this experiment was to study whether Miko I robot with simplified facial features shows face-sensitive N170 or corresponding VPP ERP neurophysiological response to different emotions, similar to the full hybrid-face robot.

1) Experimental Design: Miko I was placed approximately 90 cm away from the participants on a desk. The experiment setup is similar to the one shown in Fig. 3. Neurophysiological responses to four emotions: 1) angry; 2) happy; 3) sad; and 4) surprised, were tested. We selected these four emotions because they are far apart on the 3-D affect space axes (see Fig. 2) and showed strong N170 ERPs with the hybrid-face robot. The emotion stimuli were sent to Miko I via its companion mobile app manually at the beginning of each EEG trial. During each EEG trial, Miko I displayed the emotion for 4 s followed by a break of 4 s. The order of the sent emotions was randomized to avoid anticipation of the next emotion. A camera co-registered with EEG recording was placed facing Miko I that recorded Miko's emotions, which was later used to extract the exact time of onset of the stimulus (emotion) shown by Miko I. During a 4-s break period, Miko showed neutral expression and blinked regularly. The movement of Miko was restricted and the lights and sounds presented by the Miko during different emotions were switched off as they provide additional multimodal stimuli.

2) EEG Recording: EEG was recorded using TMSi Porti amplifier and EEG cap with passive electrodes (TMSi, Oldenzaal, The Netherlands). 16 unipolar channels of EEG were recorded from the locations Fp1, Fpz, Fp2, F3, Fz, and F4 (frontal), C3, Cz, and C4 (central), T7 and T8 (temporal), P3, Pz, P4, and Poz (Parietal), and Oz (occipital) according to the 10-20 international system. Channel AFz was used as common ground. EEG was recorded at 2048 Hz and downsampled to 256 Hz during analysis. 60 EEG trials were recorded for each of the four emotions for each participant.

TABLE III
EMOTION RECOGNITION ACCURACIES (%) FOR MIKO ROBOT

	Happy	Sad	Angry	Afraid	Surprise	Tired	Stern	Disgust
Happy	93.3	0	0	0	0	0	0	6.7
Sad	0	93.3	0	0	6.7	0	0	0
Angry	6.7	0	93.3	0	0	0	0	0
Afraid	0	6.7	0	80.0	13.3	0	0	0
Surprise	0	0	0	6.7	73.3	0	0	20.0
Tired	0	0	0	0	0	86.7	13.3	0
Stern	0	0	6.7	6.7	0	6.7	40.0	40.0
Disgust	0	0	0	6.7	6.7	6.7	46.7	33.3

3) ERP Analysis: EEG was filtered between 0.1 and 45 Hz using the fourth-order zero-phase shift band-pass filter to remove DC offset and high-frequency noise. Artefacts were removed using independent component analysis from EEGLAB toolbox [68]. The independent components containing mostly ocular artefacts were identified manually and removed. The artefacts removed EEG was segmented into epochs −100–400 ms after the stimulus onset. The stimulus onset was extracted from the video of Miko emotion changes. The video was recorded at 30 FPS and hence, the stimulus onset time was identified within ±33.33 ms of its actual onset. The mean of the 100 ms prestimulus was used as the baseline for normalization. Any trial with an amplitude above $\pm 70\ \mu$V was excluded from further analysis. Each trial was then filtered between 1–5 Hz to obtain the ERPs. Since occipito-temporal EEG channels were not available for detecting N170, we studied its corresponding simultaneously occurring face-sensitive VPP component in central region. The VPP ERP for each emotion was extracted through the grand average of time-locked EEG trials across all participants at channel Cz.

E. Experimental Results of Emotive Response to Miko I

1) Behavioral Response to Miko I: Table III shows the confusion matrix of Miko I emotion recognition accuracies by participants in percentage during the forced-choice emotion recognition experiment. The expressions happy, sad, angry, and tired showed the highest recognition rates. Other expressions showed lower recognition rates. Particularly, participants confused stern with disgusted more than half of the times and showed the lowest recognition rates. Other emotions that were generally confused were stern with tired, disgusted with surprised, and surprised with afraid. Interestingly, the recognition rate of emotion afraid in Miko I showed significant increase compared to the hybrid-face robot.

Overall, the results of recognition were in agreement with the results of the hybrid-face robot. Recognition accuracies were higher for happy, angry, and sad and lower for stern and disgust than the corresponding recognition accuracies for the hybrid-face robot. We hypothesize this small difference is a result of loss of mouth, which might add critical information for recognition of stern and disgust.

2) Physiological ERP Response to Miko Robot: All participants showed distinct changes in neurophysiological markers in response to Miko I robot depicting different emotions. We observed face-sensitive ERP component VPP in EEG in response to Miko I emotions. Due to difference in the EEG recording system of this experiment, occipito-parietal channels

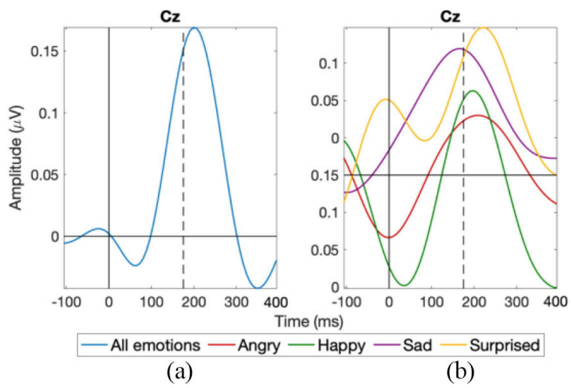

Fig. 7. VPP ERP responses to Miko I expressions. (a) Grand-average VPP waveform for all emotions together at Cz. (b) Grand-average VPP waveform for individual emotions at Cz.

were not available for detection of N170 and hence, we studied simultaneously occurring face-sensitive VPP at Cz. Grand-average VPP responses to different emotions were observed in channel Cz as shown in Fig. 7. Strong positive potentials were observed around 170 ms in central regions as expected. This shows that the Miko I robot with simplified facial features also successfully evoked face-sensitive ERP responses similar to that of hybrid-face robot with detailed facial features, such as mouth, eyebrows, nose, and ears. VPP peaks of different emotions were observed between 160 and 225 ms and were not significantly different as evaluated by ANOVA, consistent with the hybrid-face robot. The exact latency of VPP could not be determined, though latency appears to be delayed in Fig. 7, because we extracted onset of different expressions of Miko I using a 30 FPS video leading to in identification of stimulus onset within ± 33.33 ms of the actual onset. The 3-D hybrid-face robot from first experiment also showed slight delay in N170 latencies and hence, some of the delay in 3-D Miko VPP latency is consistent with this. Thus, physiological responses to Miko I were similar to those observed for the hybrid-face robot and simplification of facial features did not affect the ERP component.

F. Development of Miko II

We are iteratively developing Miko to improve its design, features, and functionality. Miko platform uses a digital screen to depict facial features and expressions and hence, is very flexible, which allows upgrading facial graphics. Following successful results of our emotion recognition research study and positive feedback from consumers, upgraded version, Miko II was developed and recently released, which incorporated more hybrid-face facial features. Miko II has more expressive eyes with eyelids that implement pupil dilation system similar to hybrid-face robot and has a mouth to depict different emotions more clearly (see Fig. 8). These facial graphics were inspired by hybrid-face robot but again redesigned to enhance its visual appeal to children as a commercial product. Having proved N170 ERP response and high recognition rates via studies with hybrid-face robot and Miko I, we expect high recognition rates for Miko II

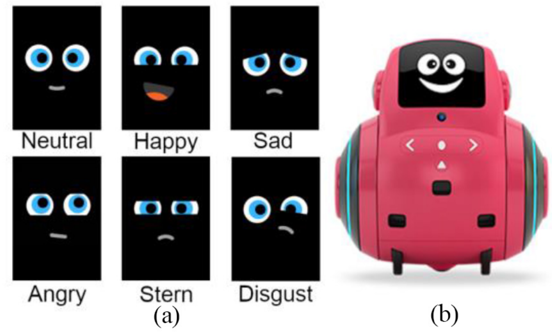

Fig. 8. Miko II design. (a) Upgraded facial design that shows more expressive eyes and mouth [69]. (b) Full product with different pupil sizes and mouth.

expressions as well since it incorporates features from both robots; experiments for Miko II are out of scope of this work.

G. IoT capabilities of Miko Robot

Miko, built upon core concepts of the hybrid-face concept, is an intelligent social robot cloud-based platform with IoT capabilities to communicate multiple devices in homes, such as mobile phones and television simultaneously. Miko has a cloud-based speech engine and can conduct conversations in four different languages. Miko can seamlessly connect with other devices in home such as television and provide a multidevice learning platform, which can be accessed simultaneously to communicate with tutors and complete learning exercises in sync. Miko can be accessed as a smart speaker. Miko is equipped with range of sensors, including camera, proximity sensor, ambient light sensor, inertial sensors, odometer, time of fight range sensor, and capacitive touch sensor and provides telepresence functionality. Miko has computer vision capability to identify, remember, and recollect known faces, objects, and surroundings. Miko's cloud platform also hosts external educational apps and allows multimodal interaction using gesture control, natural language, and mixed reality. It continuously adapts its behavior and expresses emotions by updating information from surroundings and cloud, learning preferences and using natural emotive cues from children. Miko can connect to multiple mobile devices to relay child's data securely with end-to-end encryption to parents. The development of Miko is an iterative and ongoing process and its flexible platform enables addition of new features and functionalities with ease. In the future releases, Miko will have additional capability to communicate with other IoT devices in home environment and adapt its behavior according to the surroundings.

IV. Discussion

A. Summary of Findings

In this study, we designed, validated emotional response, simplified, and commercially translated a hybrid-face robotic system. We investigated and quantified human physiological response to digital facial expressions from two versions of the robot: 1) a hybrid-face robot research platform and 2) Miko I, its simplified version commercial release.

Trust in social robots is an important factor in successful collaborations with humans. Robot's performance and attributes have more contribution in establishing trust than other human or environmental factors [70]. Trust is typically achieved in human interactions using emotions and similar approach could enhance human–robot engagement [71] by enabling robots to convey emotions via facial expressions. However, it has also been reported that increasing social and emotional capabilities of robot can cause humans to have unrealistically high expectations from social robots [72], which upon unfulfillment can decrease trust and hence a balanced approach is essential. As the use of social robots in the form of digital assistants has become a commonplace, it will be interesting to conduct a future study to explore and quantify the effect of robotic facial expressions on trust as compared to voice-only social robots and assess users' perception of trust in robots with and without face.

An optimal balance must be achieved between realistic appearance and iconic appearance of robot. The state space for developing affective robot face is huge; hence, based on the pragmatic approach, we have made assumptions to simplify this space to create a hybrid-face robot that gives illusion of depth without compromising the simplicity of design and implementation. Since developing a fully actuated face was not practical, we simplified it by developing a hybrid face with similar features. This hybrid face was still not practical for commercial applications and hence, we simplified it even further to develop Miko I robot, which still captured the core of human–robot interaction as demonstrated by high emotion recognition accuracies and face-sensitive VPP ERP.

We assume that there are different levels of abstraction for developing a facial robot in increasing order as follows: human face, fully actuated face, hybrid face, simplified hybrid face, and digital avatar. Intuitively, people respond better to a face that shows depth. Hence, we designed hybrid-face robots that gave perception of depth with faceplate without actuation on the face. By studying participants' conscious response (through emotion recognition tasks) and then evaluating their subconscious response (through ERP), we found that nonactuated depth-based robots give predominantly face-sensitive N170 and VPP responses, which are well-established ERP responses primarily to different face stimuli [41], [43]. It must be noted that though predominantly face-sensitive, these N170 and VPP ERP components have also been observed in response to several common objects stimuli, though their amplitude is attenuated and latency is delayed for nonface stimuli [43], [44], [73]. Our experimental design also allowed participants to move their head and explore 3-Dity of the robot, which can be paralleled to real human interaction. Including depth in the design of hybrid-face robot helped in building the context, which is important to enhance human–robot interactions. Though we found the depth in representation of the robot's face is useful pragmatically to create better affective experience, further work will be needed to quantify its effect.

B. Hybrid-Face Robot Validation

First, we examined the utility of hybrid-face robot with 3-D printed faceplate and digital display as a platform for human–robot engagement. As an attempt to verify the functionality of the hybrid-face robot, and to gain insights into mathematical representations of affective potential, emotion recognition experiments were carried out. Participants were able to identify different emotions with high accuracies. The animation and realism features could be fine-tuned in the future work to increase expression recognition. The hybrid-face design is very flexible and adaptable to incorporate new expressions.

We demonstrated the ability of the digital facial expressions to effectively convey emotion to a human observer by recording ERPs in EEG to determine the perception of digital emotion. We found significant difference in ERP due to the context presentation using monitor and the hybrid-face robot; thus, depth may play a role in neurophysiological response to stimuli. We ensured that participants were naive to the research questions to avoid bias in face processing known to occur due to context and manipulation by an emotionally laden task [74].

A distinctive N170 component was reliably identified in the grand-average response from all participants, for all hybrid-face robot emotions. A simultaneous positive potential (VPP) was also observed at central region (Fig. 10 in Appendix B). The digital facial expressions were able to modulate the ERP response despite having low information bandwidth. Our results are consistent with previous studies [47], [48] of the human response to conveyed emotion, which state both pleasant and unpleasant expressions evoked a larger N170 ERP response than neutral expression and this change in activity is located on the right parietal brain area (Fig. 10 in Appendix B). These results are in line with other trials conducted with human images (including our ERP validation in Fig. 9 in Appendix A), though our results for the robot's facial expressions are modulated with a lower amplitude and increased latency, congruent with a similar study by Dubal [75], who found that robot expressions are encoded as early as human faces but evoke a later and muted response. This indicates that several neuron clusters associated with internal features and head detection maybe engaged requiring additional time to acquire configural information. Positive emotions were evoked earlier than negative, which follows the current literature.

An average delay of $\sim$7 ms occurred in physiological responses between the two sources of computer monitor and the hybrid-face robot. This might be caused due to the increase in configural information or a delay as attention is refocused to the hybrid face. While a fixation cross was presented on the monitor, subjective comments from participants noted that focusing attention was easier and more natural for the hybrid face with head and ears, which helped setting the configuration parameters.

These results show considerable promise because participants were able to identify most of the expressions and responded positively to hybrid-face robot interaction. Participants quickly accepted digital facial expressions causing their attention to evolve beyond robot's physical characteristics. Thus, we propose a novel method to quantify human–robot engagement using empirical N170/VPP ERP measure.

Pupil dilation is an often overlooked dimension of nonverbal communication that can influence perceived emotion. We added pupil dilation to the hybrid-face robot in the attempt to improve conveyance of emotions by increasing the DoF without adding actuation based on our pragmatic assumptions. Inclusion of pupil dilation feature is inconclusive currently and it is difficult to determine whether it helps with the confidence of emotion recognition and requires further investigation. Participants noted that they were not aware of how dramatic the effect of pupil size was on the overall demeanor and interpretation of robot's expressions. Varying the size of the iris may impact the expected dilation of the pupils for different emotional expressions. The current eye color of the digital face provides a definite contrast between the light blue iris and black pupil that even with increased pupil dilation, gives the appearance of a cold stare for some facial expressions. The results from this experiment provide average estimations of pupil dilation to robot's facial expression that will help improve emotion recognition rates in further experiments.

C. Simplification of Hybrid-Face Robot for Mass Market

Acceptability of engaging with the hybrid-face robot by human participants and high recognition rates of different emotions presented by the hybrid-face robot was promising. However, the hybrid-face approach was still not viable for incorporating in a commercial product, which required further simplified face. Thus, the hybrid-face robot influenced the development of a commercial social robot Miko I capable of affective conversations by creating further abstractions of emotion representation. Here, we studied Miko's ability to convey different emotions and human response to those emotions and compared those with the results of the hybrid-face robot by repeating the same set of experiments. Even though Miko I had simplified facial features with just two eyes, the behavioral and physiological experiments showed comparable results to a full hybrid-face robot. Thus, Miko I was able to convey emotions successfully using static, singular expressions with eyes only, simplifying affect space representation. Miko I has integrated IoT capabilities to enable affective engagement with children for educational purposes. The conversational ability of Miko I, which is not investigated in this study, may benefit greatly from using the appropriate expressions to enrich the affective information content in the conversation and enhance engagement with humans. Similar to hybrid face, participants reported that the curvature and ears on Miko I representing facial structure providing contextual information helped in associating with the humanoid form and in recognising expressions.

The physiological study of human responses to Miko emotions also showed a distinct face-sensitive VPP ERP component during all the emotions. This validates the findings of simplified hybrid-face principle and its translation to Miko I. The amplitude of VPP was smaller because our EEG itself had an overall smaller amplitude due to difference in the EEG amplifier and referencing scheme [45]. The latency of VPP could not be estimated accurately because the time of stimulus onset was extracted from a video with 30 FPS giving stimulus onset time within $\pm$33.33 ms of actual stimulus onset. However, the VPP latency in 3-D Miko robot was delayed, which is consistent with the delay in N170 latency observed in 3-D hybrid-face robot. Strongest and most delayed ERP was obtained for emotion surprised, which was represented by bigger eye size than other emotions; however, participants showed some uncertainty in recognition of this emotion. Thus, experiments with Miko showed a successful practical application of hybrid face in affective social robot with IoT and demonstrated evoked response to visual human–robot affective interaction on a physiological level.

Based on these findings, we argue that simplified robotic platforms fusing static mechanical design and digital encoding can evoke conscious and subconscious emotive response in human beings. We support these arguments with qualitative assessment of human response and empirical analysis of their neurophysiological perception.

D. Affective Response and IoT Impact

Features, such as facial depth and humanoid physical characteristics, were positively perceived in all versions of the robot, which was critical in translation. We have shown similarities in perception of the extra dimension in all versions of the robot that evoke similar human reactions. This compromise for the first-generation commercial product was drawn from extensive qualitative surveys with the target users. The same experiments with both platforms show a comparable system despite the simplifications, including neurophysiological (EEG) experiments showing parallels in response. Commercially, future plans call for incremental improvement that incorporate more of the detail of the hybrid face robot. We also stress that the first product release specifically targeted children. Other versions of the system are being developed for both research and commercial applications, which may incorporate more hybrid face features. Human-like depth features are being considered in new applications such as interaction for cognitive stimulation and mental health.

We recognize that modifications for mass-market universally demand the exclusion of some features tested on a bespoke research platform. The purpose of this investigation was to narrow which features are most likely to be negatively perceived if excluded. We report this successful balance in social robotic interaction with children. Similar compromises in other areas will likely be dictated by the application. For example, medical applications are more tolerant to higher cost and more bespoke production, hence full static facial features are being considered in those arenas.

Our existing system enables robotic communication with multiple devices in home, such as televisions and mobile devices simultaneously over Internet network and Bluetooth to accomplish learning-based tasks. It coordinates schedules with other Internet devices to modify its behavior, allow itself to be remote controlled, remind users deadlines, assist with homework, and contact other people or use other smart technology. Speech and corresponding affective emotional conveyance are executed via cloud interface, which is updated remotely such that onboard processing is streamlined. The connection is pervasive, and the robot mines the Internet and environment to determine its interactions. This infrastructure for IoT capability remains a key enabler for future human–robot-environment information flow enabling adaptive interaction. We have illustrated a complete evolution process of conceptualization of affective robot to its translation to a commercial product with extended functionalities by enhancing it with IoT. In the future releases, Miko will have further IoT capabilities as demonstrated by its flexible cloud-based platform. Furthermore, we are also extending the work in areas such as engagement with the elderly and support of dementia patients in smart homes based on this IoT connectivity. Finally, we note that the new social robot platform Miko, now that it is available worldwide, may serve researchers as a platform for new studies based on this work. All these studies extend the from this investigation. We believe it represents a foundation for a very wide range of future work in both academic research and commercial arenas.

V. Conclusion

We have presented a complete project life cycle, from concept, to design, implementation, testing, validation, and commercial translation of hybrid-face robotic system capable of evoking affective response in users. A first-generation affective hybrid-face robot is developed to help researchers design intelligent systems capable of ensuring mutual trust, safety, and effective cooperation with humans. We successfully applied this hybrid face to develop a commercial IoT social robot, Miko I, by providing it with the ability to integrate affective information in its interactions. The qualitative and quantitative assessment of both the hybrid-face robot and its application to Miko I demonstrated that human participants were able to recognize the emotions conveyed by the robots with high accuracy and also showed neurophysiological predominantly face-sensitive N170 and VPP ERP responses in their EEG. This validated the effectiveness of emotion conveyance by social robots.

In summary, new contributions of this investigation include as follows.

1) Establishing that "hybrid face" robots are capable of emotional state conveyance with high accuracy.
2) Derivation of a canonical set of facial DoF, including pupil dilation, for deployment of affective robotics in real-world environments with IoT capabilities.
3) Introduction of two models, categorical and affect space, for representing robotic expressions.
4) Introduction of the use of empirical recording of EEG neurophysiological response to quantitatively assess human–robot visual affective interaction via studying predominantly face-sensitive N170 and VPP ERP components in EEG.
5) Demonstration of useful approach for practical commercial translation of affective IoT human–robot interface systems leading to a new mass market robotic product.

Since the time of these experiments, a new robot with greater autonomy (Miko II) drawing on these findings has been released. Future work will involve implementing Miko II and other forms of the hybrid-face robot to accelerate learning in children and as a support tool for the elderly in isolation. We also offer the new commercial platform, Miko II, as a tool for further research in social robotic interaction as an alternative to design and fabrication of bespoke research platforms.

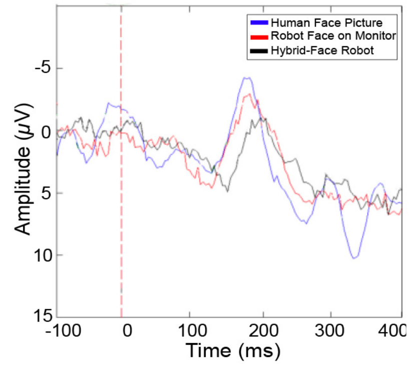

Fig. 9. Comparison of grand-average N170 ERP response to digital face presented on monitor and hybrid-face robot, and pictures of a human face at P8.

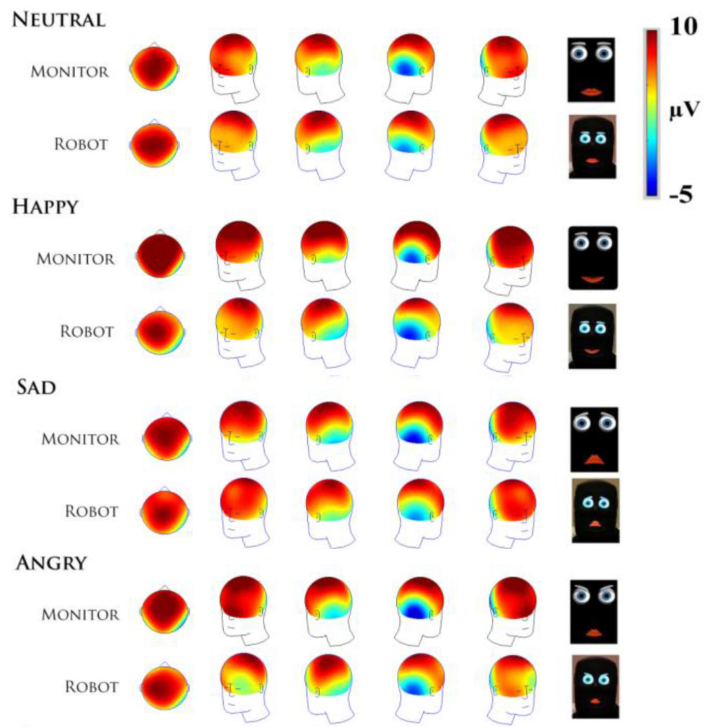

Fig. 10. EEG topography of evoked negative N170 ERP response in time window between 130 and 230 ms after stimulus onset to expressions neutral, happy, sad, and angry presented on monitor and hybrid-face robot.

Appendix A
Comparison of N170 ERP Response to Hybrid-Robot Face and Pictures of Human Faces

Fig. 9 shows comparison of N170 ERP response to hybrid-face robot and pictures of human facial expressions taken from Japanese Female Facial Expression database [65] with FACS expressions at channel P8 in three participants. This was conducted with a small subset of participants to validate our ERP paradigm and observe whether human faces show the expected face-sensitive N170 response. A strong N170 ERP is obtained for human faces as well as for the hybrid-face robot and its digital presentation on monitor. Latency of N170 of hybrid-face robot was delayed and its amplitude attenuated as compared to human faces and digital robot face on monitor.

Appendix B
EEG Topography Map of Different Stimuli

Fig. 10 outlines multiple views of EEG topography showing spatial location of ERP responses to neutral, happy, sad, and angry expressions for monitor and robot stimuli sources. Negative potential (N170) is observed in the occipito-temporal region (around P8) and the corresponding positive potential (VPP) is observed simultaneously in the central region (around Cz). The digital expressions on monitor evoked larger N170 and VPP as compared to expressions on robot. Happy and angry emotions evoked larger amplitude N170 and VPP.

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