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iAware: A Real-Time Emotional Biofeedback System Based on Physiological Signals

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ABSTRACT Self-awareness is the foundation of emotional intelligence. Most people can recognize their own and others' emotions. However, many people suffer from a common infirmity that prevents them from recognizing emotion within themselves and are therefore unable to experience a life that fulfills them emotionally. We propose a real-time mobile biofeedback system that uses wearable sensors to depict five basic emotions and provides the user with emotional feedback. We also present empirical results for the configuration of a physiological signal-based emotion recognition system in two experimental scenarios involving controlled and noncontrolled environmental settings. In our evaluation, we show that iAware helps increase emotional self-awareness by reducing the predictive error by 3.333% for women and by 16.673% for men. The primary results suggest the usefulness and necessity of the iAware system to provide users with real-time biofeedback based on physiological signals.

INDEX TERMS Emotion recognition, live biofeedback, real-time mobile computing, physiological signals, self-awareness.

I. INTRODUCTION

"Rule your feelings, lest your feelings rule you," Syrus [1]. User emotion plays a critical role in the decision process, which leads to individual satisfaction. Emotional inspiration, which seems to be a primary human motive [2], can be considered from a functionalist perspective [3]. In fact, emotions are primarily motivating forces that start with arousal processes and then direct activity [4]. Emotions influence the judgments, priorities, and actions of individuals [5].

Salovey *et al.* [6] defines emotional intelligence (EI) as the ability to perceive and express emotions, to understand and use emotions, and to manage emotions to foster personal growth. EI focuses on how individuals identify, understand, express, regulate, and use their own feelings and those of others [7]. In [8], Goleman addressed five domains for EI: knowing one's own emotions, managing emotions, motivating oneself, recognizing emotions in others, and engaging in relationships. He considers self-awareness a "keystone" of EI. Self-awareness is the foundation of enhancing positive emotions and improving quality of life. From an EI perspective, self-awareness is the first step in exerting emotional self-control for containing, ordering or controlling emotions. By recognizing a feeling as it develops, one can then properly address that feeling. Self-awareness gives us the ability to identify the feelings of others based on previous experiences with similar feelings, and thereby gives us the ability to manage emotions in others or, at least, to show empathy [8].

Most people can regulate their own and others' feelings [9]. However, a common infirmity affects people who cannot recognize emotion in themselves and are therefore unable to experience a life that fulfills them emotionally. For example, individuals reporting greater emotional clarity and a greater ability to repair their emotional states report higher levels of self-esteem and mental health [6]. In contrast, individuals who have lower levels of emotional clarity or who are unable to regulate their emotional states show poorer emotional adjustment [3]. Thus, this paper proposes a real-time biofeedback system with wearable sensors to depict five basic emotions and provide the user with "emoji" feedback corresponding to the proper emotion to help the user develop self-awareness to effectively modulate their behavior, reduce bias related to self-processing, and promoting a sustainable and healthy mind.

The remainder of this paper is organized as follows: Section II explains the background work on emotion recognition and live biofeedback (LBF). Section III describes the methods and materials used, including the emotion detection module, the emotion biofeedback module, and the evaluation methods. Section IV demonstrates and discusses our results. Section V presents some concluding remarks and describes possible future studies.

II. RELATED WORK

A. EMOTION RECOGNITION

The classification of emotion has been mainly studied based on two fundamental viewpoints: basic and dimensional. The basic emotion viewpoint posits that all feelings can be derived from a limited set of universal and innate basic emotions that show distinct physiological patterns that are cross-cultural and user-defined, called stimulus-response specificity (SRS) [10]. The reported accuracy was 70% for classifying three emotions (calm, positively excited, and negatively excited) [11], 75% for classifying four emotions (neutral, sadness, fear and pleasure) [12], 45% for classifying six emotions (amusement, contentment, disgust, fear, neutral, and sadness) [13], and 50% for classifying nine emotions (anger, interest, contempt, disgust, distress, fear, joy, shame, and surprise) [14]. Clearly, the model is more complex when it handles more emotions, thereby reducing accuracy.

Alternatively, the individual response specificity (IRS) model was proposed by Russell and Pratt [15] in 1980. In the dimensional approach, emotions can be described based on three dimensions: pleasure, arousal and dominance (PAD). Since this method was first proposed, it has been widely employed in a large number of studies on emotion [16]–[19]. The highest accuracy was approximately 96% for arousal and 94% for valence using very high volumes of features extracted from heart rate variability (HRV), respiration (RSP) and electrocardiogram-derived respiration (EDR) signals and principal component analysis (PCA) for dimensional reduction [20]. Most current systems map the two dimensions into two or three classes within arousal-valence areas. When using two classification schemes, the classes are ''high'' and ''low'' for arousal and ''positive'' and ''negative'' for valence. When there are three classes, the classes are ''calm'', ''medium'' and ''activated'' for arousal and ''unpleasant'', ''neutral'' and ''pleasant'' for valence [21], [22]. The dimensional approach can capture a particular aspect of one's internal state but not the entirety of emotion; however, it is not necessary to map dimensional spaces into a specific emotion, as this approach captures what emotions have in common but not what is unique to a specific emotion. For example, fear and anger share unpleasant and aroused feelings but differ in terms of the external causes and behavioral reactions; thus, the model may not capture the difference between them.

To overcome this problem, a hyper theory combining both dimensions and emotion categories was postulated [23]. Using this hyper theory, the hyper approach mostly utilized four classes to map emotions into each different quarters of a two-dimensional plane [16], [24], [12], [25]. Moreover, Albraikan *et al.* [26] proposed an ensemble approach based on a stacking model that allows multiple emotion models and learning algorithms to be jointly embedded within a user-independent model. The first base model used was the model developed by Ekman [27], which utilizes autonomic measures to map reactions to emotional stimulus labeling. The second base model used is a hyper model established by Russell [23] and Yik *et al.* [28], which utilizes self-reported labels for induced emotion annotation. Ensemble methods were used on top of the two basic models to learn a high-level classifier. The system achieved overall accuracies of 65.6% for 5 emotions and 94.0% and 93.6% for recognizing valence and arousal emotions, respectively, using the MAHNOB dataset.

B. LIVE BIOFEEDBACK (LBF)

In 1970, Green *et al.* [29] introduced a psychophysiological principle of live biofeedback (LBF). Biofeedback refers to practices that aim to measure the biological activities of the human body and feed information back to the user to increase personal awareness about such physiological processes. Feedback can address at least one of the five traditional senses. The most commonly used form of LFB is visual feedback. Al Osman *et al.* [30] adopted this concept in a biofeedback closed-loop system by continuously monitoring mental stress levels by measuring heart rate variability (HRV), breathing rate and activity level. They provided feedback through serious games for stress management. The feedback was presented in the form of a tree representing the status of the autonomous nervous system of the user. Jercic *et al.* [31] presented an auction game to train subjects in emotion regulation strategies. The game difficulty was adjusted by the player's physiologically measured arousal level. The user can gain an awareness of their emotional state and the influence of his/her emotions on decision making through a financial context using heart rate (HR) data. The second most common form of feedback is auditory feedback. Millings *et al.* [32] developed neurofeedback software that transfers the data received by the sensor and emits a pleasant, waterfall-like sound to the user. The volume of the sound depends on the power of the alpha frequency band of the user's electroencephalography (EEG) spectrum divided by the power in the beta band of the spectrum. The user can then try to learn how to control the volume of the waterfall sound by increasing their alpha power relative to their beta power as a stress management strategy. Other studies have used a combination of sensory data, such as visual and auditory [33], visual and tactile [34], or auditory and tactile [35] combinations. The biofeedback concept has found uses in several research fields, such as driving [36], financial decision making [37], and well-being [32].

There are two distinct domains for LBF: foreign-live biofeedback (FLBF) and self-live biofeedback (SLBF). Interested readers can refer to the review in [38]. The study of FLBF aims to enhance social interaction. The majority of studies used wearable devices, such as a t-shirt [39], a glove [40], or a bicycle helmet [41], while others used

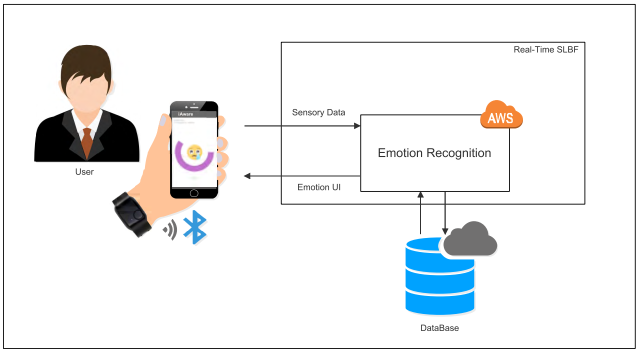

FIGURE 1. The iAware emotion monitoring system.

mobile device applications [42] as a medium to increase feelings of social presence.

In the study of SLBF, a large body of literature has demonstrated LBF for affects and emotions indirectly through the paralinguistic features of speech ([43], [44]), through user behavior ([45], [46]), or through the direct use of wearables ([30], [32]). The study of self-emotion LBF using physiological signals is divided into the arousal dimension and the valence dimension. A high volume of studies targeted the arousal dimension. Most of these studies focused on the management of stress, such as mental stress [30], tension [47], or depression [32], while others examined factors that are considered the opposite of stress, such as the level of relaxation in [48]. In contrast, few studies have focused on the valence dimension for emotion regulation. In most cases, it is designed for scenarios that are known to potentially trigger high levels of arousal, such as in [31], [49], and [50], while others addressed specific emotion regulation strategies, as proposed in [37] and [51]. Real-time emotion recognition using physiological signals is usually impossible to implement because of the complexity related to sensor placement, data analysis, and accuracy [52]. A large number of studies chose to use emotional biofeedback. However, to the best of our knowledge, no existing studies have reported the use of emotion recognition within LBF.

III. METHODS AND MATERIALS

By considering the biofeedback system of Al Osman *et al.* [30], Figure 1 shows the continuous monitoring of emotion using physiological signals.

A. HARDWARE

An Empatica E4^{TM} sensor was used to collect subjects' physiological signals [53]. This sensor is a wireless, flexible, easy-to-use device that is worn on the wrist and is employed to track the sympathetic branch of the autonomic nervous system in a rapid, facile manner. It is a multisensor device for real-time computerized biofeedback and data acquisition. The E4 wristband has four embedded sensors: a photoplethysmography (PPG) sensor, an electrodermal activity (EDA) sensor, a 3-axis accelerometer, and an infrared temperature sensor. These sensors collect and report critical information on human performance and health parameters, including EDA, also known as the galvanic skin response (GSR), which is sampled at 4 Hz, blood volume pulse (BVP), which is sampled at 64 Hz, acceleration (32 Hz), HR (1 Hz), and skin temperature (4 Hz). For data analysis, four channel signals, i.e., EDA, HR, interbeat interval (IBI), and temperature, were used. We relied on the E4 API, which extracts HR, and IBI features because the E4 sensor has two built-in algorithms that extract this information. The data is available through the E4 connect dashboard in near-real-time via Empatica's mobile APIs. All data are resampled at 64 Hz.

B. EMOTION DETECTION MODULE

Multisensor data fusion is a well-established research area in the emotion detection domain. There is widespread literature addressing sensor fusion at different levels and using diversified approaches; readers are referred to the survey in [54] for further information on this topic.

In this study, we employed a hybrid data fusion approach using weighted multidimensional DTW ($WMDDTW$) [26]. The optimization method is used to minimize the warping windows of each warping path and the segmentation of the time series and to assign a weight to each diminution to overcome the limitations of DTW_I.

$$WMDDTW(T,S) = \sum_{d=1}^{k} w_d \times |DTW(T_d, S_d, ww_d)|. \tag{1}$$

where $WMDDTW$ is the cumulative distance of all dimensions of two k-dimensional time series, T and S, independently measured under DTW. w_d is the weight that was assigned to each diminution d. $DTW(T_d, S_d)$ is defined as the DTW distance of the d^{th}-dimension of T and the d^{th}-dimension of S.

In equation (1), each dimension is considered independent, and DTW is allowed to warp each dimension independently of the others with respect to the warping window parameter ww_d. The $WMDDTW$ classifier calculates a distance matrix between the two k-dimensional time series, T and S, according to a warping window parameter ww_d and the dimension weight w_d. $WMDDTW$ uses a 1-NN algorithm to find the smallest distance and returns the corresponding label associated with that S_d sample within S.

C. EMOTION BIOFEEDBACK MODULE

For the feedback, we used a combination of sensory data. Visual feedback was provided using an emoji-based version of the emotions wheel [55]. Sherine [56] developed an emoji-based version of the emotions wheel for Emotive UI. The wheel is a combination of the standard Plutchik wheel and emotional value associations to each color using emojis that reflect the emotional spectrum; see Figure 2. We also employed tactile feedback using haptic feedback. The vibration intensity was set from low to high based on the emotional intensity. The fear emotion was set to high, and the happy

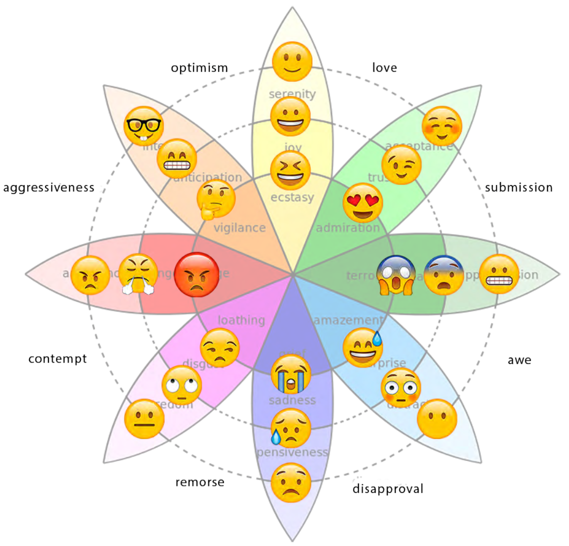

FIGURE 2. **Emoji-based version of the emotion wheel [55].**

emotion was set to low, while the neutral state was set to zero. We designed two experiments: one was a controlled experiment, and the other was a noncontrolled test.

D. EVALUATION

For statistical analysis, we used the nonparametric method. We used McNemar's test, also referred to as the within-subjects chi-squared test, for two reasons. First, McNemar's test is a useful tool for comparing two different models to test the significance of the difference between two paired results of matched individuals. Second, the test is recommended for small sample sizes [57]. We study the effect with respect to the responses of gender groups and emotion types for cases with and without using the iAware system. The *P* value was calculated using a 2×2 contingency table from the McNemar's test with the continuity correction [58]. McNemar's test approximates the binomial exact P-value using χ^2, as in equation (2):

$$\chi^2 = \frac{(|B - C| - 1)^2}{B + C} \tag{2}$$

where B is the total number of cases where the self-report fails to detect the emotion but iAware passes, and C is the total number of cases where iAware fails to detect the emotion but the self-report passes for the same person.

In addition, the two models were compared to each other using video emotion detection. We also checked the plausibility of the iAware SLBF using an offline textual questionnaire organized into two sections, with the first section including multiple-choice questions and the second section including open-ended questions. In the first section, all six questions were answered on a discrete scale from 1-5, where 1 denotes the lowest plausibility, and 5 denotes the highest plausibility.

During the experiment, the mobile system receives real-time data via Bluetooth, sends the signal data securely encrypted to a cloud service for data analyses, and then provides the user with biofeedback related to their emotion.

1) SHORT EXPERIMENT

HYPOTHESIS

The goal of this study was to test our hypotheses that the iAware system can improve self-awareness by measuring the clarity and attention to emotions of users according to self-reports. In our opinion, the validity of self-reports of emotion is questionable. Here, we follow Brody and Hall [59], who concluded that men and women display gender-stereotypical expressions. There are individual differences in awareness of and willingness to report on emotional states, which potentially compromises the emotional experience. Men exhibit restrictive emotionality [60]. Restrictive emotionality refers to a tendency to inhibit the expression of certain emotions and an unwillingness to self-disclose intimate feelings [61]. Moreover, women report more intense emotional experiences and more overt emotional expressions across 37 cultures [62]. We hypothesize that the user will experience an increase in emotion self-awareness while using the SLBF from the iAware system by comparing the discordant pairs resulting from the iAware and the self-report.

PARTICIPANTS

A total of twenty healthy participants took part in this experiment, including ten men and ten women. This sample size is recommended as an appropriate size for quantitative usability studies [63]. The ages of the participants ranged from 18 to 58 years old. None of the participants had experienced symptoms of excessive sweating (hyperhidrosis) or hypokalemia (bradycardia or tachycardia) or had a known history of heart disease. None were experiencing any mental health problems or taking antianxiety or antidepressant medications. Our experiment received ethical approval from the Research Ethics Board of the University of Ottawa. All participants were informed about the procedures and potential risks before beginning the experiment.

a: UNCONTROLLED EXPERIMENT

EXPERIMENTAL SETUP

We evaluated the users' self-experience in a neutral setting for 20 participants. While the participants were using the application and data were being collected, each participant was asked to report their feeling in the moment, first without feedback and then with the iAware real-time feedback. Finally, they were asked to what extent the application was able to explain their inner feelings and represent their emotions.

b: CONTROLLED EXPERIMENT

We formulate the null hypothesis that the probabilities are the same, i.e., that neither model performs better than the other. Thus, the alternative hypothesis is that the performances of the two models are not equal. If there is no association between emotion detection based on automatic detection by

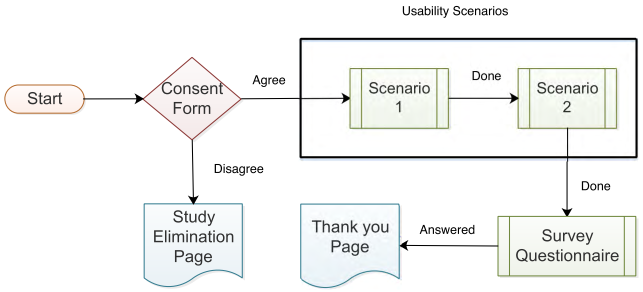

FIGURE 3. The controlled experiment procedures.

the iAware system and the user's perceived emotion by the self-report methods, what is the probability of observing a significant discrepancy between the two methods based on the discordant pairs?

EXPERIMENTAL SETUP

Figure 3 shows the experimental procedures. For each participant, the experiment involved a session lasting approximately 15 *min*. The experiment was designed with the following steps: an initial phase, emotion detection without biofeedback, and emotion detection with biofeedback. First, the researchers explained the experimental procedures and any risks associated with participation. Before the trial was initiated, each participant was required to wear the E4 wristband on his or her nondominant hand. Then, the participant completed a consent form. After that, benchmark data were collected. This step was optimized to last approximately 110 *s*, according to previous work, and was followed by a sufficient visual stimulation period lasting 40 *s* for each targeted emotion and the self-report using AniAvatare [64].

For the stimulus material, we chose EMDB [65] because videos contain more emotional content than a single image. We randomly selected two clips from the three categories of happy, sad, and fear. We used movie clips 4007 and 4009 for the happy condition, 3009 and 3008 for the sad condition, and 1007 and 1008 for the fear condition. All clips had sound to maximize the emotional experience. We randomly chose one of these clips for each scenario.

This test has two scenarios while watching emotional movie clips: detection of the emotion without any feedback and detection of emotion with feedback using the iAware system. Each participant was asked to watch one 40-s movie clip in each of the three categories. After each clip, they reported their emotion using AniAvatare [64] and then completed a satisfaction survey. The questionnaire serves to evaluate the system and capture the user's feedback after using the system.

2) LONG EXPERIMENT

PARTICIPANTS

A total of four healthy participants took part in a neutral setting experiment, including two men and two women. Their ages ranged from 18 to 58 years old. None of the participants had experienced symptoms of excessive sweating or had

TABLE 1. Results per subject for an uncontrolled experiment without feedback; the emotions are (1) neutral, (2) happy, (3) sad, (4) love, and (5) fear.

Subject#	Gender	Felt emotion	App Detecting
1	M	2	2
2	M	2	2
3	M	1	1
4	M	1	5
5	M	2	2
6	M	1	1
7	W	1	1
8	M	1	1
9	W	2	1
10	W	1	1
11	W	5	5
12	M	2	2
13	M	1	5
14	M	2	2
15	W	1	5
16	W	1	1
17	W	2	2
18	W	2	2
19	W	1	1
20	W	1	3

a history of heart disease or any mental health problems. To perform statistical analysis, we need a benchmark for comparison with the result. Therefore, in the following, we assessed one user's self-experience while watching a soccer match. As the benchmark, we used half-time analysis provided during the 2018 FIFA World Cup in Russia [66]. The match report not only has a minute-by-minute event analysis but also provides a statistical analysis, including ball position heat maps and shot counts. We have informed consent to compare the results using the video emotion detection tool of the Microsoft Azure API.[1] Face API is a cloud-based tool that allows one to detect, identify, analyze, and organize emotions and tag faces in a video.

IV. RESULTS AND DISCUSSION

Figure 4 shows the visual feedback for each emotion, i.e., (a) neutral, (b) happy, (c) sad, (d) love, and (e) fear. The intensity of the emotion is shown in a circular progress view with colors that match the emotion wheel [55], including light gray for neutral, yellow for happy, purple for sad, green for love and blue for fear.

A. SHORT EXPERIMENT

1) UNCONTROLLED EXPERIMENT

We evaluated 20 participants who felt emotions in a neutral setting. Table 1 shows the results per subject for an uncontrolled experiment without feedback. Then, we compared

[1] https://azure.microsoft.com/en-ca/services/cognitive-services/emotion/

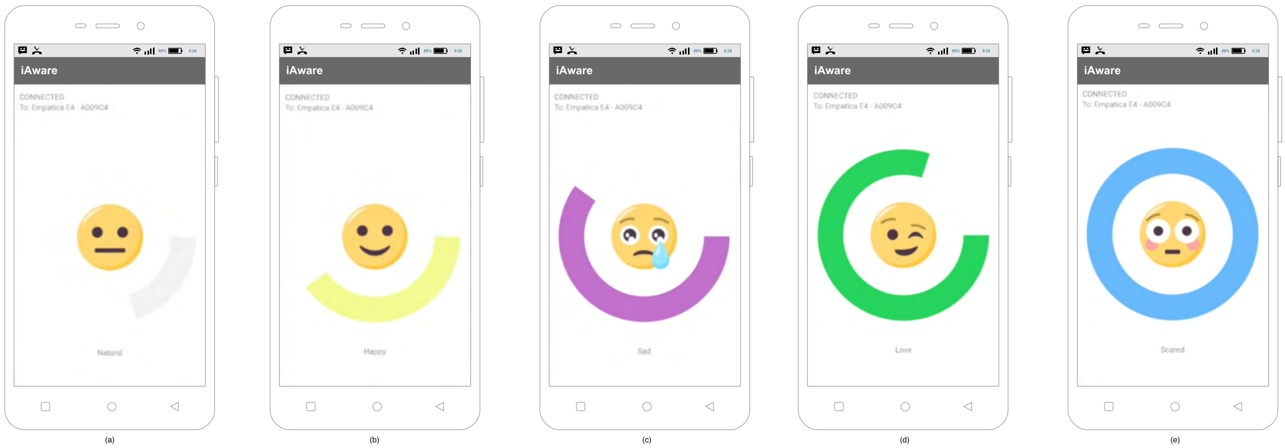

FIGURE 4. **iAware visual feedback: (a) neutral, (b) happy, (c) sad, (d) love, and (e) fear.**

these results with the results obtained after the participants received feedback.

Table 1 shows the results per subject. There were five discordant pairs for emotion detection between the iAware system and the self-reported results. After receiving the feedback, participants 4, 13, and 15 reported that they were more nervous during the experiment. In contrast, participant 20 reported feeling sad, which was not expected to be caught by the application. Moreover, participant 9 stated that she had more overt emotional expressions, as she was feeling positive neutral. This evidence may support the gender-stereotypical expression of emotions; therefore, iAware SLBF can potentially increase self-emotional awareness. Participants 4,13,15 and 20 are examples of inhibiting the expression of fear and sadness, while participant 9 is a classic example of a woman reporting more intense emotional experiences.

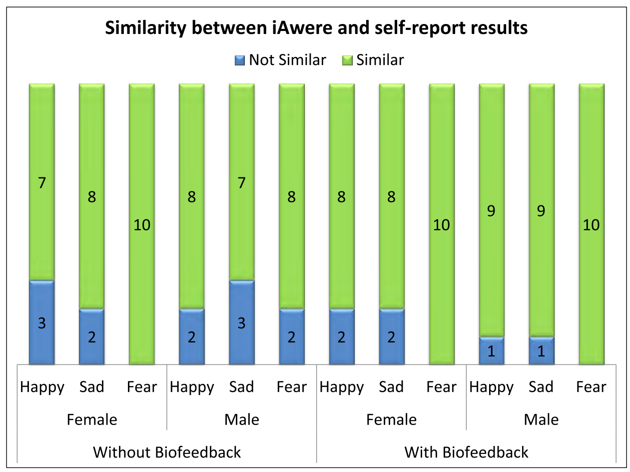

FIGURE 5. **Similarity between iAware and self-reported results.**

2) CONTROLLED EXPERIMENT

We studied 120 cases for a total of 20 subjects. Figure 5 shows the results of the analysis using McNemar's test. Table 1 and Figure 6 show the results of the analysis using the postexperiment questionnaire. A 2 × 2 matrix with factors of gender (men and women) and reporting tool (system and self-report) was developed to report the results for the emotions (happy, sad, and scared).

For the first case scenario without using the SLBF, there were 12 discordant pairs for emotion detection. There were 10 (83.333%) pairs for which the iAware system was able to detect emotion correctly but the self-report was not, and 2 (16.667%) pairs for which the self-report was correct but the iAware system was not. The two-tailed P-value was 0.0433, the Chi-squared statistic was 4.083 with 1 degree of freedom, and the odds ratio was 0.2000 with a 95% confidence interval of 0.021 to 0.939.

For the second case using the SLBF, there were six discordant pairs for emotion detection. There were 5 (83.333%) pairs for which the system was able to detect emotion correctly, but the self-report was not, and 1 (16.667%) pair for which the self-report was correct but not the iAware system. The two-tailed P-value was 0.2207, the Chi-squared statistic was 1.500 with 1 degree of freedom, and the odds ratio was 0.200 with a 95% confidence interval of 0.004 to 1.787.

By conventional criteria, in the first scenario, since the P-value is smaller than our assumed significance threshold (α=0.05), we reject the null hypothesis and assume that there is a significant difference between the two predictive models. In the second scenario, since the P-value is larger than our assumed significance threshold (α=0.05), we cannot reject the null hypothesis and assume that there is no significant difference between the two predictive models.

Moreover, McNemar's test provided further insight regarding model selection. We are interested in the two cases for which the results from both the iAware system and the self-report agreed. Figure 5 graphically summarizes the analysis of the gender factor and effect type of different emotions.

TABLE 2. Average results for the postexperiment questionnaire.

Question #	Question	Average
1	iAware Mobile feedback feature is effective	4.20
2	The App was able to detect my current feelings most of the time	4.05
3	The App feedback is helping me become self-aware of my feelings	4.10
4	Knowing my emotions is helping me to focus on regulating my emotions	4.20
5	I would use this App in a daily basis	3.90
6	I would recommend this App to my friends and family members	4.10

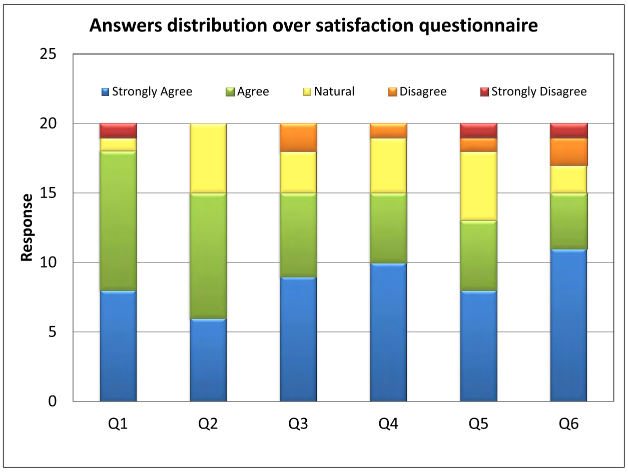

FIGURE 6. Distribution of answers to the satisfaction questionnaire.

Studying single emotions revealed that there was a noticeable 3.333% reduction in the discordant pairs resulting from the self-report bias.

Analysis of the gender factor revealed a similar result to that of [62]: some women report more intense emotional experiences for happy emotions. In addition, some men exhibit restrictive emotionality, particularly for feelings of sadness and fear, which is similar to the results of [60]. Overall, iAware SLBF can potentially increase awareness related to gender-stereotypical expression, reducing the predictive error by 3.333% for women and by 16.673% for men. Analysis of emotion signals showed similar findings to those reported in [60]. For swomen, there was no significant difference with and without SLBF for sadness and fear, while for men, there was no significant difference for happiness. In general, participants using iAware perform substantially better than the model without SLBF.

In the postexperiment questionnaire, regarding participant satisfaction, the first six questions were based on a Likert scale and prompted participants to specify their opinions on various aspects of interactions by selecting one of five options. Table 2 present the questions and the average results for the postexperiment questionnaire. The average plausibility score for all questions was 4.05 of 5. Figure 6 summarizes the results of the postexperiment questionnaires. Interestingly, 18 participants reported that they would use the iAware system every day, and 17 participants said that they would recommend it to friends and family members.

For the open-ended questions, we asked users to describe in their own words whether they would like to know their current emotion. Interestingly, when asked this question, some users associated the question with increased awareness, for example, "*I would like to know how to control my emotions so that I don't overreact*", "*Sometimes my emotions are unclear, and using this system can help*", "*Yes, to control myself and to know I have to make a decision*", "*It helps better regulate my feelings*", and "*It helps me know more about myself*". One particular participant stated that "*Sometimes, I would like to know how exactly I feel, but sometimes, the system can make me stressed*". The results indicate that the SLBF from the iAware system appears to positively affect self-awareness.

We also asked users whether they would like others to know about their current emotion. Participants reported mixed feelings about this question. Some users answered "yes" to show a self-awareness connection with others to seek their support; for example, participants reported "*Only for asking for help*", "*Only if they are going to help*", and "*Yes, so that others can know when something makes me happy or sad and so that they will respond accordingly*". The participants also highlighted the importance of context, especially social context; for example, "*It depends on who is going to see my emotions*", "*Not all the time; sometimes, I want to keep my emotions private*", and "*Only close family members so that they can understand my reaction*". The users' answers to this question suggested that FLBF may help increase emotional awareness for oneself and others; however, the issue of privacy is an essential element that must be considered, given responses such as "*It depends, I guess; mostly No, as I prefer to keep my emotions personal*", and "*No, it is private*". People may vary in their ability to perceive and understand other people's emotions, which may affect their ability to recognize and manage social situations. iAware is potentially useful in easing interpersonal interactions using FLBF, which is driven by sending and receiving social cues to make it easy to infer these cues. FLBF can also help amplify social cues and increase people's sensitivity towards such cues.

B. LONG EXPERIMENT

To perform statistical analysis in a neutral setting, we used the 2018 FIFA World Cup analysis as a benchmark to compare the iAware results. Therefore, in the following, we analyzed one subject for 45 minutes while watching the Argentina vs. Nigeria match during the 2018 FIFA World Cup. Figure 7 shows video images captured for emotion

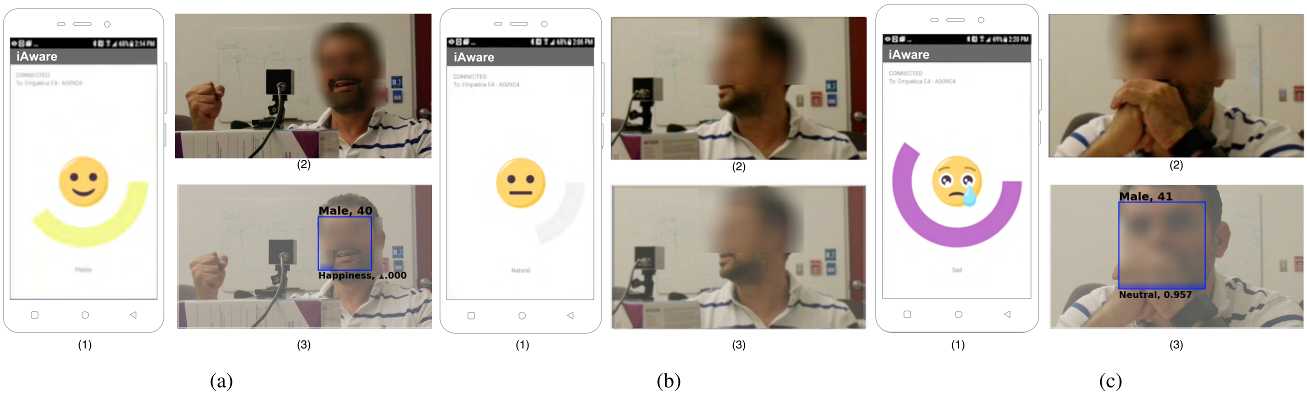

FIGURE 7. Example results of the analysis: (1) iAware, (2) Original video, and (3) Microsoft Azure. (a) Stimuli: Argentina scored the first goal. (b) Stimuli: Conversations with a friend. (c) Stimuli: Argentina's player injured.

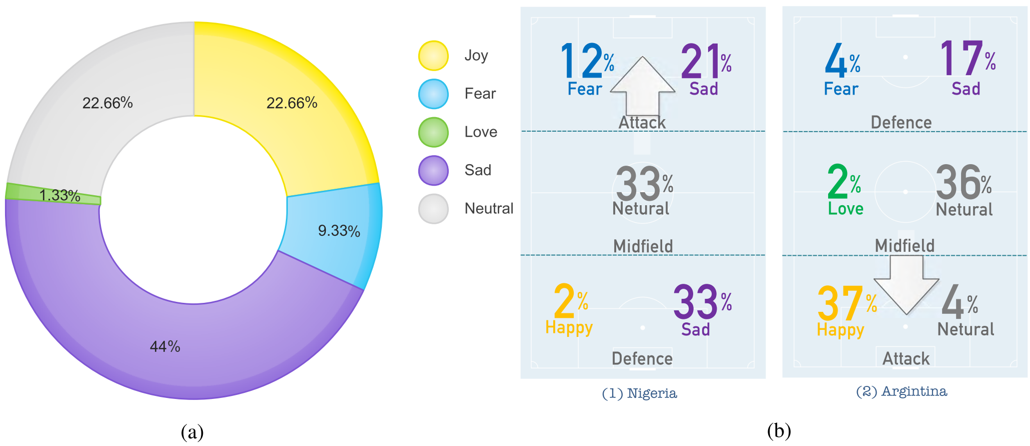

FIGURE 8. Half-time statistic of the soccer ball match between Argentina and Nigeria; the total may not be 100% due to rounding. (a) Emotion's percentage. (b) Emotion heat map based on the ball Possession.

recognition using the Microsoft Azure API. Figure 8 shows the results of the analysis comparing iAware with the half-time statistical analysis.

Figure 7 shows example results of the analysis comparing video detection with iAware detection. In general, iAware performs similarly to video detection; however, in some cases, iAware shows substantially better results than the model based on video detection in neutral settings, allowing the user more mobility and freedom. The Azure API was not able to analyze some cases: for example, when the user began jumping for joy after the first goal scored by Argentina, when the user cupped his hand over his mouth, which occurred several times during the match, and when the user turned his face and extensively moved during conversations.

Figure 8.a highlights the emotion percentage throughout the match, during which he felt 22.66% neutral, 44% sad, 9.33% fear, 22.66% joy, and 1.33% love. Figure 8.b shows the emotion heatmap based on ball possession using [66]. For Argentina, the user was 37% happy each time that the team attacked and 4% neutral. He also felt 36% neutral most of the time during the midfield battle. There was one case (2%) when the user felt love, which occurred when he saw his favorite player, Mr. Diego Maradona, on TV. In contrast, the user felt 17% sad when Argentina was defending and 4% fear when Nigeria almost scored a goal. For Nigeria, the user felt 12% fear each time they almost scored and 21% sad when they attacked. He then felt 33% neutral when the ball was in the midfield, He felt 2% happy when the defender missed the ball, allowing Argentina to take a good shot; however, he felt sad one-third of the time (approximately 33%) during defending, as Argentina primarily lost good opportunities. This result suggests that iAware could be a useful tool for detecting emotion in an uncontrolled environment.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented an evaluation of the plausibility of the emotions detected by an LBF system using physiological signal-based emotion recognition. The overall results of the evaluation reveal an overall positive impact of the system on self-awareness. Thus, this system can provide real-time monitoring of emotions at any time and in any place, providing the user with more mobility and freedom. The design and implementation of iAware allow it to be easily adapted for SLBF or FLBF using a cloud service.

In future work, we plan to integrate more customized feedback. The emotion recognition system could also incorporate a combination of emotions and multimedia for applications in other technological fields, such as computer gaming, special education, and social networks.

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