

# Ubiquitous emotion-aware computing

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**Abstract** Emotions are a crucial element for personal and ubiquitous computing. What to sense and how to sense it, however, remain a challenge. This study explores the rare combination of speech, electrocardiogram, and a revised Self-Assessment Mannequin to assess people's emotions. 40 people watched 30 International Affective Picture System pictures in either an office or a living-room environment. Additionally, their personality traits neuroticism and extroversion and demographic information (i.e., gender, nationality, and level of education) were recorded. The resulting data were analyzed using both basic emotion categories and the valence–arousal model, which enabled a comparison between both representations. The combination of heart rate variability and three speech measures (i.e., variability of the fundamental frequency of pitch (F0), intensity, and energy) explained 90% ( $p < .001$ ) of the participants' experienced valence–arousal, with 88% for valence and 99% for arousal ( $ps < .001$ ). The six basic emotions could also be discriminated ( $p < .001$ ), although the explained variance was much lower: 18–20%. Environment (or context), the personality trait neuroticism, and

gender proved to be useful when a nuanced assessment of people's emotions was needed. Taken together, this study provides a significant leap toward robust, generic, and ubiquitous emotion-aware computing.

**Keywords** Ubiquitous computing · Emotion · Unobtrusive sensing · Speech features · Heart rate variability · Personality

## 1 Introduction

It has been 40 years since Skinner [88] said: *The application of the physical and biological sciences alone will not solve our problems because the solutions lie in another field. ... It is not enough to “use technology with a deeper understanding of human issues,” or to “dedicate technology to man's spiritual needs,” or to “encourage technologists to look at human problems.” ... What we need is a technology of behavior. ... But a behavioral technology comparable in power and precision to physical and biological technology is lacking ...* (p. 4–5).

Since Skinner's words [88], much has changed, but even more has not. On the one hand, *phenomena of private experience, whether they be characterized as mental or emotional, conscious or unconscious, are inaccessible to direct public observation; the actions of living organisms, on the other hand, can be observed directly and studied in relation to antecedent conditions in the same way as the phenomena treated in other sciences* (p. 3) [72]. This was the case four decades ago, and still is the case, despite the impressive progress of cognitive sciences and neuroscience [85] (e.g., brain imaging techniques [60, 104] and brain–computer interfaces [8, 17, 91]). On the other hand, technologies ranging from biosensors to robots have become

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smaller, even miniaturized [70], and can be integrated into virtually all products (e.g., clothes [89] or our homes [101]). Consequently, new branches of science and engineering have emerged, such as personal and ubiquitous computing (UbiComp) [50], ambient intelligence (AmI) [20], pervasive computing [12]), wearable computing [2], and the Internet of Things [34, 48] (also known as physical computing, haptic computing, and things that think).

The true potential of the emerging branches of science such as UbiComp and AmI is more than an engineering paradigm. The envisioned systems can only be realized if human behavior can also be analyzed automatically. Subsequently, the resulting knowledge can be utilized for the integration of humans' inputs and outputs with those of their media. This yields *intuitive computing* and brings us to one of its core notions: (human) emotions. This has long been accepted by psychologists but has only been embraced by science and engineering, since Picard's book *Affective Computing* in 1997 [79]. As a result, ambient sensing of emotions [97], emotion-aware consumer products [96], and affective interaction [31] have been proposed. This is what this article will be about.

Emotions can be transmitted either overtly (e.g., by the face, the body, or the voice), covertly (e.g., biosignals), or in a combination of both [26]. On the one hand, the complex nature of emotion is illustrated by the absence of an integral model of (human) emotions (cf. [26]). So, it is still largely unknown what cues humans process in determining others' emotional states. On the other hand, the processing of signals related to emotions has been a topic of research for more than a century [25, 51, 57]. Until the end of the twentieth century, attention to this relation, however, was limited and, hence, so was progress [26] (cf. [24]).

In this article, five issues will be addressed that are troubling the development of ubiquitous emotion awareness:

1. A broad range of physiological signals, speech, and computer vision techniques are employed to determine people's state of emotions. Regrettably, despite the rapid growth of such techniques, these methods are either obtrusive, sensitive to noise, or both [32, 94].
2. What emotions are, how they can be described, and how they are expressed remain difficult to define [25, 38, 57, 72].
3. Although it is generally agreed that environment (or context) is of the utmost importance [7], laboratory and field research in this field are seldom compared [39, 53, 99].
4. Personality traits are seldom taken into account (e.g., [43, 80, 109]), although widely recognized as being important [67, 90, 99].

5. Demographic information (e.g., age [63, 83], gender [49, 104], culture [11, 35, 69], social class [35, 69], and nationality [68]) and ethnics [11, 87] are known to possibly influence experienced emotions and their accompanying physiological responses. Nevertheless, this basic information is often disregarded.

By addressing the combination of these issues, we expect to contribute significantly to emotion-aware technology.

In the next section (Sect. 2), we will briefly introduce the construct emotion and two models of emotion that are often used in emotion-aware computing. Next, in Sect. 3, we will discuss signals of emotion and introduce the hybrid approach chosen in this research. Subsequently, in Sect. 4, we will introduce the study conducted. Section 5 will describe how the different types of signals are processed. Next, the results and their interpretation will be described in Sect. 6. We will close, in Sect. 7, with a general discussion.

## 2 Emotions

A complete bookstore could easily be filled with books and articles on emotion and related topics. Reviewing this vast amount of literature falls beyond the scope of the current article. Moreover, excellent handbooks (e.g., [25, 57]) and review articles (e.g., [24, 38]) have already been published on this topic. So, no overview of emotion theories and their levels of description will be provided. Instead, we will work toward a stipulative definition of emotion. This is necessary as there is *still no consensus on a definition of "emotion," and theorists and researchers use "emotion" in ways that reflect different meanings and functions* (p. 363), as Izard recently stated [38]. This overview takes up a special section of the journal *Emotion Review* as foundation [38].

### 2.1 On defining emotions

In the search for consensus on what emotion is, Izard [38] identified six key structures of emotion, namely: (1) neural systems, (2) response systems, (3) feelings, (4) expressive behavior, signalling systems, (5) antecedent cognitive appraisal, and (6) cognitive interpretation of feelings. Moreover, seven functions of emotions were identified: (1) facilitates attention and direction of responses, (2) motivates cognition and action and provides emotion information [73], (3) alters the salience or value of an event to facilitate adaptive associations, (4) contributes to emotion and behavior regulation, well-being, and the safeguarding of sensitivities and concerns, (5) social signaling and

communication, (6) provides a neural (often conscious) workspace for assembling solutions, and (7) different emotions (and their structures) have different functions. Together, these aspects and functions of emotion provide a knowledge space we can work with.

Izard [38] concludes by stating that *Emotion consists of neural circuits (that are at least partially dedicated), response systems, and a feeling state/process that motivates and organizes cognition and action* [73]. *Emotion also provides information to the person experiencing it, and may include antecedent cognitive appraisals and ongoing cognition including an interpretation of its feeling state, expressions or social–communicative signals, and may motivate approach or avoidant behavior, exercise control/regulation of responses, and be social or relational in nature.* (p. 367) [38]. This does not provide us with a precise definition of emotion as a unitary concept. However, it does provide us something to hold on to and work with. Moreover, more than anything else, it emphasizes both the complexity of emotions and their ubiquitous nature.

## 2.2 Modeling emotion

As we outlined in the previous section, emotions are complex to untangle. However, there is general consensus on the neural systems underlying them, which are at least partly dedicated [38]. This having been said, emotion recognition remains challenging for both man and machine. For example, different emotions and different structures of each emotion have different functions [38], and neural systems are influenced by much more than solely emotions (e.g., imagine what happens to your heart rate when you start walking).

For engineering practice, a workable model of emotion needs to be adopted. However, there are good arguments to state that such a model is beyond science’s current reach. Nevertheless, some model needs to be chosen; otherwise, signals of emotion cannot be processed and classified and our endeavor ends prematurely. Psychology distinguishes two emotion models: (1) discrete emotion categories and (2) a (2D or 3D) continuous dimensional model of emotion.

The discrete emotion categories originate from Darwin’s pioneering work on basic emotions. The theory behind this model assumes that these emotion categories are hard-coded into our neural system and recognized universally [19, 28, 56] (cf. the debate on color categories as unveiled by Berlin and Kay [82]). Although still a topic of debate, most consensus exists on the six emotion categories happiness, sadness, surprise, fear, anger, and disgust.

The (continuous) dimensional model of emotion assumes orthogonal unipolar or bipolar dimensions that together can describe the emotional state a person is in.

Most often Russel’s circumplex or valence–arousal (VA) model of emotions [18, 27, 33, 66, 84] is adopted. This distinguishes arousal and valence (i.e., pleasure/displeasure) as two orthogonal bipolar factors that describe emotions. The dimensional VA model has frequently been extended [14, 33]; for example, to enable the incorporation of mixed emotions [16, 68, 96, 102]. These extensions often incorporate two unipolar valence dimensions: one for positive and one for negative valence, instead of one bipolar valence dimension. Such extended VA models incorporate three dimensions, instead of two. This approach was also adopted for the current research.

## 3 Ubiquitous signals of emotion

As we already mentioned in the introduction, the techniques usually employed to process signals of emotion are often either obtrusive, sensitive to noise, or both. We will now discuss each of the three signals: biosignals, computer vision, and speech and identify their pros and cons. Next, we will introduce the hybrid approach adopted in the research described in this article.

Features of physiological signals (or biosignals) are known to indicate emotions [15, 32, 95]; however, measurement of such signals is often experienced as obtrusive by participants.; for example, facial electromyography (EMG) requires sensors to be placed on the face, and electrodermal activity (EDA; or galvanic skin response, GSR) requires sensors to be placed on participants’ hands or alternatively on their foot soles. Not only is their application obtrusive and do they prevent normal functioning but these sensors also frequently drop off when used in ambulatory settings. Until recently, this has prevented biosignals being incorporated into consumer products. However, with the progress of wearable computing and wireless sensing technologies in the last decade, this problem quickly vanishes [2, 23, 37, 58, 64, 75, 77, 106, 110]. In parallel, biosignal recording, even with a certain amount of obtrusiveness, is embraced by the general public in Western societies (e.g., real-time ECG processing to guide athletes). Hence, the path toward biosignal-based emotion-aware computing would seem to be paved.

An alternative for biosignals are computer vision techniques. These can be employed both as a static (i.e., image) and a dynamic technique (i.e., video) [36, 103, 107, 109]. Moreover, one can choose to conduct markerless recordings or to use markers, which facilitate processing the images or videos. Most research on emotion-aware computing incorporates recordings of the face, but body language analysis also has been shown to be a rich source of information (e.g., movements and gestures) [6, 36, 47, 61]. Although appealing, computer vision techniques are only

usable for emotion recognition in very stable environments; for example, without occlusion, in stable light sources, and with the users sitting at a desk or on a couch [99, 103]. Hence, in practice, in ambulatory settings, computer vision-based emotion-aware computing is not feasible.

Speech-based emotion-aware computing is probably the most exhaustively studied technique of this triplet. Its early studies included humans as classifiers, followed by advanced statistical procedures, and, subsequently, automated digital speech signal processing by computers [29, 86, 92, 105, 109]. Speech can be considered as an indirect biosignal that is very well suited to unveil the emotional state of a person. Non-speech utterances have also been shown to be of interest for emotion-aware computing [78]; however, they are relatively unexplored. The audio recordings used for speech processing suffer from various types of noise. Therefore, speech-based emotion recognition is most often conducted in well-controlled (laboratory) environments. However, advances in source localization and, subsequent, noise cancelation are promising. Hence, we anticipate the feasibility of speech-based emotion-aware computing in the near future.

Signals from the first group (i.e., biosignals) are rarely combined with signals from the other two groups (i.e., computer vision and speech). In contrast, biosignals themselves are frequently combined (e.g., [43, 80, 98]). Also, signals from the speech processing and computer vision groups are frequently combined [22, 76, 109]. However, some exceptions exist. Bailenson et al. [5] combined computer vision and physiological measures. Van Drunen et al. [100] combined physiological measures with eye tracking, thinking aloud, and user–system interactions (cf. [99]).

The current study combines speech and biosignals for emotion recognition. To the author's knowledge, only two groups have reported on this combination: Kim et al. [41, 42, 44, 45] and the current author and colleagues [97]. A possible explanation is the lack of knowledge of the application of this combination of measures. We expected to extract features from both the speech and the ECG signal of people's experienced valence and arousal, as well as on their basic emotions. Let us now briefly introduce both of these signals.

The human speech signal can be characterized by various features and their accompanying parameters. However, no consensus has thus far been reached on the features and parameters of speech that reflect the emotional state of the speaker. Most evidence exists for the variability (e.g., standard deviation; SD) of the fundamental frequency ( $F_0$ ), the intensity of air pressure ( $\mathcal{I}$ ), and the energy of speech ( $\mathcal{E}$ ) [29, 86, 92, 105, 109]. Therefore, we have selected these speech features in the current research.

The electrocardiogram (ECG) is an autonomic signal that cannot be controlled easily, as is the case with electrodermal activity [15]. ECG can be measured directly from the chest. Where Blood Volume Pulse (BVP) can already be recorded rather unobtrusively for some time, it would seem that it will also be possible soon for ECG [58, 77]. Previous research identified various features of ECG as indicators for both experienced valence and arousal [3, 15, 18, 71]. However, most evidence is provided for the HR variability (HRV) [40]. HRV decreases with an increase in mental effort, stress, and frustration [15, 100]. Moreover, HRV can be influenced by the valence of an event, object, or action [3, 71, 81]. On the whole, HRV, as can be derived from ECG, is a rich source of information and has been shown to be a powerful discriminator between emotions [40]; therefore, HRV was selected as the ECG's feature.

## 4 Method

### 4.1 Participants

40 volunteers (20 men, 20 women [49]; average age 27.8; SD 7.6; range 18–49) participated. None of them had hearing impairments or any known cardiovascular problems. All had (corrected to) normal vision. The participants were ignorant of our research goals.

The participants were divided into two groups of 20 each. One group of participants was assigned to an office environment, in which they took place in an office chair. The other group of participants was assigned to a living-room environment, in which they sat on a couch. At both locations, the room was silent and darkened, and a screen was placed in front of the participant. Although both environments were controlled, this enabled an operationalization of the concept context (or environment) and, hence, its influence on ubiquitous emotion-aware computing.

After instructions, the participant signed an informed consent, and the ECG measurement belt and headset were positioned. Next, the participant read aloud a non-emotional story to (a) verify by asking whether or not the participant had understood the instructions, (b) to test the equipment, and (c) to determine their personal baseline for both the speech and the ECG signal.

Using a questionnaire, we recorded general demographic information of the participants: age [55, 63, 93], level of education, and nationality [87]. This information was used to control for them as possible sources of influence [99]. Next, the participants were also asked to fill in a revised, short scale of the Eysenck Personality Questionnaire (EPQ-RSS) [30]. Two binary indices were derived

from the EPQ-RSS. These indicate the participants' personality traits neuroticism and extroversion, which are both known to influence the emotions experienced [21, 62, 65, 97].

### 4.2 International Affective Picture System (IAPS)

To elicit an emotional response, the participants looked at 30 pictures from the IAPS [52]; see Table 1 for their identification numbers. The IAPS set is based on a dimensional model of emotion [18, 52, 66]; however, as has been shown, this set also has great potential to reflect multiple emotion categories [97, 66]. Moreover, this set of pictures has been thoroughly and repeatedly validated [52, 66] and, as such, serves as a sort of ground truth for emotion research. The pictures were randomly presented on a 15.4 inch TFT screen (1280 × 800 pixels, 60 Hz refresh rate; video card: ATI Mobility Radeon 9700).

Each of the 30 IAPS pictures (see Table 1) were shown for a duration of 20 s, which is more than sufficient for emotion assessment [96]. After the presentation of each picture, the participants had 30 s to describe it, followed by a resting period of 20 s. During these 50 s, a gray screen was shown. The experiment started and finished by displaying a gray screen during 50 s.

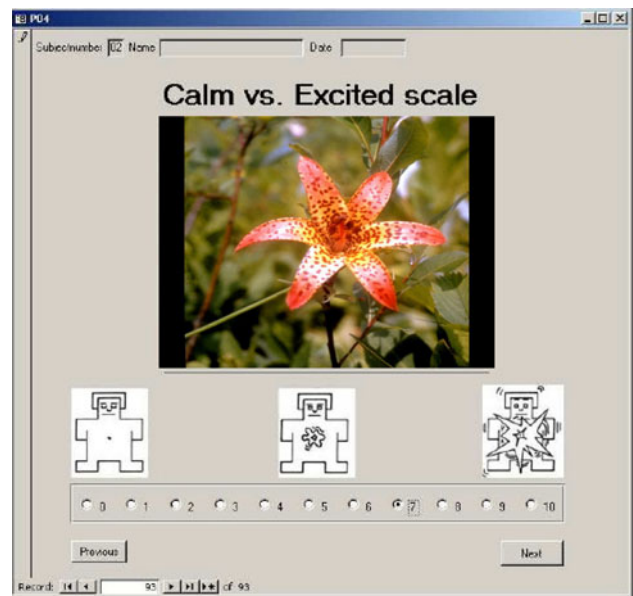
### 4.3 Digital Rating System (DRS)

After all 30 IAPS pictures were presented and the participants had described them, the participants had been asked to judge the IAPS pictures using a DRS. The DRS displayed the IAPS pictures to aid the participant's memory, together with 11 point (range: 0–10) Likert scales using

**Table 1** The 30 IAPS pictures [52] with the average ratings given by the participants on the positive valence, negative valence, and arousal Likert scales

IAPS identifiers	Basic emotions	VA model	
		Valence	Arousal
4624, 4625, 7450, 8033, 8220	Joy	Positive	High
2120, 3015, 6022, 6230, 6312	Anger	Negative	High
5000, 5020, 5030, 5800, 7900	Relaxed	Positive	Low
2141, 2205, 2375, 9220, 9435	Sadness	Negative	Low
2704, 5920, 7640, 8160, 8232	Neutral 1	Neutral	High
2214, 7000, 7041, 7484, 9070	Neutral 2	Neutral	Low

From the positive and negative valence ratings, three valence categories were derived: neutral, positive, and negative. Using the scores on arousal, two arousal categories were determined: low and high. Consequently, we were able to assess a discrete representation of the valence–arousal (VA) that distinguished six compounds



**Fig. 1** A screendump of the Digital Rating System (DRS) used in this research; see Sect. 4. An IAPS picture (category: relaxed) is shown [52]. Below the 11 point (0–10) Likert scale with radio buttons is shown augmented with three Self-Assessment Mannequin (SAM) images. With these images, the experienced arousal was assessed as indicated by both the SAM images and the text “Calm versus Excited scale”

radio buttons; see Fig. 1. The complete set of all 30 IAPS pictures was presented three times in separate blocks. Within the three blocks, the IAPS pictures were presented in random order. To each block, one of the three Likert scales (i.e., positive affect, negative affect, and arousal [96, 14]; see Sect. 2) was assigned in semi-random order; that is, the second block presented the arousal scale, the first and third block presented the negative and positive valence scales in balanced order. Consequently, the possible bias in judging the IAPS pictures was limited. The DRS' Likert scales were augmented with the Self-Assessment Mannequin (SAM) [13], of which three pictures were shown; see Fig. 1. This provided an intuitive and validated subjective assessment of the emotions the participants' had experienced.

The three scales used allowed us to construct the VA model; see also Sect. 2. In addition, it enabled us to assign the images to the six basic emotions [18, 66], see also Table 1. For each picture, the average rating on each of the three scales over all participants was calculated. This enabled a classification of the pictures into two categories (i.e., high and low) for each of the three scales: positive, negative, and arousal. From these classifications, two categories for arousal were identified: high arousal and low arousal. In addition, three categories for valence were identified: positive, negative and neutral, where the category neutral denotes neither positive nor negative valence.

Table 1 provides a specification of the emotion categories and the IAPS images assigned to them.

## 5 Signal processing

This section describes how all of the data were recorded and, subsequently, processed. Speech utterances were recorded continuously by means of a standard Trust multifunction headset with microphone. The recording was performed in SoundForge 4.5.278 (sample rate 44,100 Hz; sample size 16 bit). Parallel with the speech recording, a continuous recording of the ECG was done through a modified Polar ECG measurement belt. The Polar ECG belt was connected to a data acquisition tool (NI USB-6008). Its output was recorded in a LabVIEW 7.1 program, with a sample rate of 200 Hz.

### 5.1 Signal selection

The speech signal of three participants was not recorded due to technical problems. For one other participant, the speech signal was too noisy. These four participants were excluded from further analysis. With four other participants, either a significant amount of noise was present in their ECG or the signal was even completely absent. These participants were omitted from further processing.

Since one of the main aims was to unveil any possible added value of speech and ECG features to each other, all data were omitted from analysis of the eight participants whose ECG or speech signals were not recorded appropriately. This resulted in a total of 32 participants (i.e., 16 men and 16 women), whose signals were processed. Regrettably and surprisingly, the eight participants whose data was not processed, all participated in the office-like environment. So, 20 participants participated in this research in a home-like environment and 12 of participants sat down in an office-like environment. Conveniently, of these 32 participants, men and women were equally present in both environments.

### 5.2 Speech signal

For each participant, approximately 25 minutes of sound was recorded during the study. However, since only parts in which they spoke are of interest, the parts in which the participants did not speak were omitted from further processing.

Some preprocessing of the speech signal was required before the features could actually be extracted from the signal. We started with the segmentation of the recorded speech signal in such a way that the speech signal was determined separately for each picture. Next, the abnormalities in the

speech signals were removed. This resolved all technical inconveniences, such as: recorded breathing, tapping on the table, coughing, cleaning the throat, and yawning. This resulted in a “clean” signal.

After the selection of the appropriate speech signal segments and their normalization, the feature extraction was conducted. Several parameters derived from speech have been investigated in a variety of settings with respect to their use in the determination of people’s emotional state. Although no general consensus exists concerning the parameters to be used, much evidence exists for the SD of the fundamental frequency of pitch (F0) (SD F0), the intensity of air pressure ( $\mathcal{I}$ ), and the energy of speech ( $\mathcal{E}$ ) [29, 86, 92, 105, 109]. We will limit the set of features to these, as an extensive comparison of speech features falls beyond the scope of this study.

For a domain  $[0, T]$ , the energy ( $\mathcal{E}$ ) is defined as:

$$\frac{1}{T} \int_0^T x^2(t) dt, \quad (1)$$

where  $x(t)$  is the amplitude or sound pressure of the signal in Pa (Pascal) [10]. Its discrete equivalent is:

$$\frac{1}{N} \sum_{i=0}^{N-1} x^2(t_i), \quad (2)$$

where  $N$  is the number of samples.

For a domain  $[0, T]$ , intensity ( $\mathcal{I}$ ) is defined as:

$$10 \log_{10} \frac{1}{T P_0^2} \int_0^T x^2(t) dt, \quad (3)$$

where  $P_0 = 2 \times 10^{-5}$  Pa is the auditory threshold [10].  $\mathcal{I}$  is computed over the discrete signal in the following manner:

$$10 \log_{10} \frac{1}{N P_0^2} \sum_{i=0}^{N-1} x^2(t_i). \quad (4)$$

It is expressed in dB (decibels) relative to  $P_0$ .

Both the  $\mathcal{I}$  and the  $\mathcal{E}$  are directly calculated over the clean speech signal. To determine the F0 from the clean speech signal, a fast Fourier transform has to be applied over the signal. Subsequently, its SD is calculated; see also (5). For a more detailed description of the processing scheme, we refer to [9].

### 5.3 Heart rate variability (HRV) extraction

From the ECG signal, a large number of features can be derived that are said to relate to the emotional state of people [3, 39, 40, 95, 97]. This research did, however, not aim to provide an extensive comparison of ECG features. Instead,

the use of the combination of the ECG signal with the speech signal was explored. Therefore, one well-known distinctive feature of the ECG was chosen: the variance of heart rate.

The output of the ECG measurement belt has a constant (baseline) value during the pause between two heart beats. Each new heart beat is characterized by a typical slope consisting of four elements, called: P, Q, R, and S. A heart beat is said to be characterized by an R-wave, which is an upward deflection. The HR is calculated from the intervals between these R-waves (R–R intervals) [3, 39, 95, 97]. The measurement belt for the ECG signal appeared to be sensitive to movements of the participant. This resulted in four types of noise that can be distinguished: a heart beat that differs from the normal PQRS shape, heart beats that succeed too quickly, missing heart beats in a sequence, and no HR signal at all. The ECG signal was checked automatically for all these types of noise and corrected where necessary.

The ECG signal was segmented into separate signals per stimulus, before it was processed. Next, the intervals between the R-waves (R–R intervals) of the ECG signal were determined. Subsequently, the mean R–R interval was determined. To determine the variability of the heart rate (HRV) from an ECG, the R–R intervals of the ECG were determined. Subsequently, two methods were applied for the calculation of the HRV, namely: the variance ( $\sigma^2$ ):

$$\frac{1}{\mathcal{R}} \sum_{i=0}^{\mathcal{R}-1} (\Delta_i - \bar{\Delta})^2 \tag{5}$$

and the mean absolute deviation (MAD):

$$\frac{1}{\mathcal{R}} \sum_{i=0}^{\mathcal{R}-1} \Delta_i - \bar{\Delta} \tag{6}$$

of the R–R intervals  $\Delta_i$ .  $\bar{\Delta}$  denotes the average R–R interval, and  $\mathcal{R}$  denotes the number of R–R intervals. The SD of the R–R intervals is defined as the square root of (5):  $\sigma$ . Note that the  $\sigma^2$  as defined in (5) is identical to the total spectral power. This also explains why comparisons between frequency and time–domain measures have often shown that for every band of an HR power spectrum, there is at least one time–domain correlate [63]. Further, please note that various other measures were applied for the determination of the HRV [3, 39, 40, 63, 95, 97]. However, with these three measures, we expected to have a good indication of the use of HRV for emotion detection.

### 5.4 Normalization

To tackle intrapersonal differences in the speech signal  $x(t)$ , the feature series  $f(t)$  calculated from this signal had to be normalized. All feature series calculated were normalized by subtracting people’s personal baseline  $\mu$  from the original feature series  $f(t)$  [59]:

$$\tilde{f}(t) = f(t) - \mu, \tag{7}$$

where  $\tilde{f}(t)$  denotes the normalized feature series.

The personal baseline  $\mu$  was obtained at the start of the study, directly after the instructions; see also Sect. 4. This normalization is a standard correction that is often used in psychophysiological studies and has repeatedly been shown to work [15]. The resulting data are often denoted as delta or reaction score. These scores are known to be both suitable and reliable for absolute level comparisons.

The ECG signal was processed without normalization. A normalization of the features derived from the ECG signal is already included in the calculation of the HRV (cf. 5 and 6 with 7). Note that for many of the other features extracted from an ECG signal, normalization is required.

## 6 Results

This section discusses the results obtained in this study. First, the considerations taken in the analysis will be presented. Next, in line with the main aims of this study, we will analyze the combined discriminative power of both the combination of features (i.e., repeated measures multivariate analysis of variance (MANOVA) (Wilks’ lambda)) and the features separately (i.e., (univariate) repeated measures analysis of variance (ANOVA) (Huynh-Feldt)). This is done for two series of analysis, one to assess the dimensional VA model and one to assess six discrete basic emotions. The factors included in the analyses are as follows: environment, the personality traits neuroticism and extroversion, and gender; see also Table 2.

### 6.1 Considerations with the analysis

Preliminary analysis of the ECG signal showed that the SD, the variance, and MAD of the heart rate (see 5, 6) provided similar results. This is in line with what is reported in the literature [46, 63]. Since the preliminary analysis did not reveal significant differences among the three measures for HRV and this is supported by the literature, we have

**Table 2** Legend of the factors included in the analyses presented in Sect. 6, particular in Tables 3, 4, 5, and 6

Abbreviation	Explanation
V	Valence
A	Arousal
E	Environment (or context)
P <sub>N</sub>	Personality trait neuroticism
P <sub>E</sub>	Personality trait extroversion
G	Gender

chosen the most common one: the SD of the R–R intervals. Therefore, in the main analysis, variance and MAD of the R–R intervals as measures for HRV were excluded; see also Fig. 2. From this point on, the SD of the R–R intervals will simply be denoted as HRV.

The following factors were also included in the analysis: the environment (i.e., office versus living room), gender, and the two personality traits extroversion and neuroticism. Preliminary analysis showed that the other recorded demographical information (see Sect. 4) did not influence the emotional responses of the participants. Hence, this information was excluded from further analyses (cf. Fig. 2).

To tackle the problem of finding spurious relationships that can arise when conducting multiple tests separately, first multivariate analysis was conducted and, subsequently, univariate analysis. Note that only if multivariate analysis had revealed effects was univariate analysis to be conducted to further unravel this effect. Alternatively, this problem could have been tackled by a (modified) Bonferroni adjustment, which ensures the probability of type I

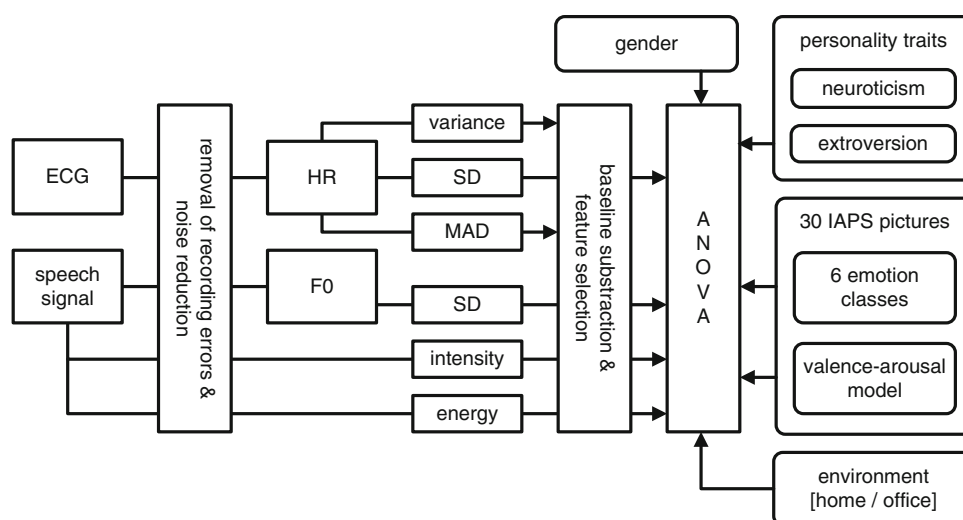
errors  $\leq .050$  [74]. However, this has the drawback that there is no consensus on the modification of Bonferroni.

All tests will be reported with their degrees of freedom, power, and level of significance. If the level of significance is close to zero, this will be denoted with  $p < .001$ , instead of providing an exact statistic. As measure of effect size partial eta square ( $\eta^2$ ) will be reported to indicate the proportion of variance accounted for (i.e., a generalization of  $r/r^2$  and  $R/R^2$  in correlation/regression analysis) [108]. The threshold for reporting results is sharp (i.e.,  $p \leq .010$ ) and, hence, ensures reliable results. Where interactions appeared that exceed the order four, they have been ignored, as they are nearly impossible to interpret. Otherwise, all interaction effects will be reported.

### 6.2 The (dimensional) valence–arousal (VA) model

In Table 3, the results of a repeated measures MANOVA are presented that mapped the four features derived from the speech and ECG model onto the dimensional VA model. Results on both the integral VA model and its two

**Fig. 2** The processing scheme of unveiling affective dimensions. It shows how the physiological signals (i.e., speech and the ECG), the emotions as denoted by people, personality traits, people’s gender, and the environment are all combined in repeated measures ANOVAs. *ECG* electrocardiogram, *HR* heart rate, *F0* fundamental frequency of pitch, *SD* standard deviation, *MAD* mean absolute deviation, and *ANOVA* analysis of variance



**Table 3** Results of the repeated measures MANOVA on the valence–arousal (VA) model and its distinct dimensions. The threshold for reporting results was  $p \leq .010$

V	A	E	P <sub>N</sub>	P <sub>E</sub>	G	Specification of effect
•						$F(8,74) = 67.835, p < .001, \eta^2 = .880$
•		•				$F(8,74) = 3.752, p = .001, \eta^2 = .289$
•			•			$F(8,74) = 4.426, p < .001, \eta^2 = .315$
•			•	•		$F(8,74) = 2.774, p = .010, \eta^2 = .231$
•		•			•	$F(8,74) = 3.419, p = .002, \eta^2 = .270$
	•					$F(4,17) = 653.941, p < .001, \eta^2 = .994$
	•	•				$F(4,17) = 9.325, p < .001, \eta^2 = .687$
•	•					$F(8,74) = 82.962, p < .001, \eta^2 = .900$
•	•	•				$F(8,74) = 4.431, p < .001, \eta^2 = .324$
•	•		•			$F(8,74) = 4.168, p < .001, \eta^2 = .311$
•	•				•	$F(8,74) = 2.895, p = .007, \eta^2 = .238$



**Table 4** Results on the repeated measures ANOVAs on the valence–arousal (VA) model and its distinct dimensions

V	A	E	P <sub>N</sub>	P <sub>E</sub>	G	Specification of effect
SD F0						
•		•	•			$F(2,40) = 6.136, p = .009, \eta^2 = .235$
•		•			•	$F(2,40) = 6.327, p = .008, \eta^2 = .240$
•			•		•	$F(2,40) = 8.135, p = .010, \eta^2 = .289$
•	•	•	•			$F(2,40) = 5.924, p = .010, \eta^2 = .229$
Intensity						
•						$F(2,40) = 817.149, p < .001, \eta^2 = .976$
•			•			$F(2,40) = 13.677, p < .001, \eta^2 = .406$
	•					$F(1,20) = 1095.287, p < .001, \eta^2 = .982$
•	•					$F(2,40) = 1060.802, p < .001, \eta^2 = .981$
•	•	•				$F(2,40) = 52.611, p < .001, \eta^2 = .341$
•	•		•			$F(2,40) = 63.491, p < .001, \eta^2 = .384$
Energy						
	•					$F(1,20) = 24.123, p < .001, \eta^2 = .547$
•	•	•			•	$F(2,40) = 5.254, p = .009, \eta^2 = .208$
HRV						
•		•	•			$F(2,40) = 6.872, p = .005, \eta^2 = .256$
•		•			•	$F(2,40) = 9.463, p = .001, \eta^2 = .321$
•			•		•	$F(2,40) = 6.354, p = .007, \eta^2 = .241$
	•	•			•	$F(1,20) = 8.493, p = .009, \eta^2 = .298$
	•		•		•	$F(1,20) = 8.772, p = .008, \eta^2 = .305$
•	•	•	•			$F(2,40) = 7.426, p = .004, \eta^2 = .271$
•	•	•			•	$F(2,40) = 9.736, p = .001, \eta^2 = .327$

The threshold for reporting results was  $p \leq .010$

dimensions are presented. Table 3 denotes that with the MANOVA, 90% of the variance of the VA model can be explained. The results on the distinct dimensions confirm this result with, respectively, 88 and 99% explained variance for the valence and arousal dimensions.

When the factors environment, the personality traits neuroticism and extroversion, and gender were included in the analysis, good results were obtained as well. However, the power of the MANOVAs and the explained variance were much lower than when these factors were ignored; see Table 3. Taken together, these results confirm the efficiency of the small set of features as compiled for this research and suggest that brute force processing and extraction of large numbers of features (e.g., >1,000 [86, 107]) are not required for emotion-aware computing.

To unravel the influence of each of the four features, a repeated measures ANOVA was executed for each of them. The results of these analyses are presented in Table 4. These analyses provide a much more subtle image of the features included in the MANOVA. We will now first discuss the results on the three speech features (i.e., SD F0, intensity  $\mathcal{I}$ , and energy  $\mathcal{E}$ ) and, subsequently, the ECG feature HRV.

SD F0 by itself had little predictive power, and even with one additional factor included, no strong results were found. When both environment and the personality trait

neuroticism were taken into account, an effect was found for the VA model; see Table 4. This effect can be mainly attributed to the dimension valence, for which SD F0 was sensitive, when two factors were included; see Table 4. For the dimension arousal, with two levels to distinguish, no effect was found.

$\mathcal{I}$  showed to have an excellent predictive power and was able to explain almost all variance with 98% for the VA model and both of its dimensions; Table 4. Also strong effects were found on the VA model and its dimension when the environment and the personality trait were taken into account. However, these effects are not even close to the magnitude of the effects found when these factors were not taken into account. So, the environment, personality traits, and gender seem to have little influence, if any, on the intensity of speech as indicator for valence and arousal.

The feature  $\mathcal{E}$  proved to be a good indicator for the dimension arousal of the VA model; see Table 4. Analysis showed that additional factors were of little influence on this effect. In addition, an effect was found on the VA model when both the environment and gender were taken into account; however, this was only marginally below the threshold of reporting. So,  $\mathcal{E}$  seems to be a good and robust indicator for experienced valence.

The ECG feature HRV is frequently used as an indicator for emotions. In the perspective of the VA model, it has

been reported to indicate both the experienced valence and the experienced arousal. These results are confirmed by the current study; see Table 4. However, for the VA model, as well as for its distinct dimensions, the factors environment, the personality trait neuroticism, and gender proved to be of influence. In contrast with the speech features, the power of HRV as indicator for the VA model was only unveiled when these factors were included in the ANOVA; see Table 4.

### 6.3 The six basic emotions

In Table 5, the results of a repeated measures MANOVA are presented that mapped the four features derived from the speech and ECG model onto the six basic emotions. The MANOVA showed an effect of the four features on the six basic emotions, with and without other factors included. The effect of the factors environment, the personality trait neuroticism, and gender were limited. The personality trait extroversion was of no influence at all.

To gain understanding in the influence of the four features, repeated measures ANOVAs were executed for each of them. The results of these analyses are presented in Table 6. First, we will discuss the results of the three speech features (i.e., SD F0, intensity  $\mathcal{I}$ , and energy  $\mathcal{E}$ ). Second, the results of the ECG feature HRV will be discussed. In none of the analyses did the personality trait extroversion show any influence; therefore, this factor will not be mentioned further on.

SD F0 by itself showed to have little predictive power; see Table 6. Only when either environment and the personality trait neuroticism or environment and gender were taken into account was an effect found.  $\mathcal{I}$  showed to have no predictive power at all, neither by itself nor in combination with other factors.  $\mathcal{E}$  showed to have a good predictive power by itself. The four factors included in the analysis were of no influence on  $\mathcal{E}$ ; see Table 6.

Of all four features, HRV showed to have the highest predictive power. However, this was only the case when two out of the three factors included were taken into

**Table 6** Results on the repeated measures ANOVAs on the six basic emotions

E	P <sub>N</sub>	P <sub>E</sub>	G	Specification of effect
SD F0				
•	•			$F(5,100) = 6.292, p = .006, \eta^2 = .239$
•			•	$F(5,100) = 6.441, p = .005, \eta^2 = .244$
Energy				
				$F(5,100) = 6.352, p < .001, \eta^2 = .241$
HRV				
•	•			$F(5,100) = 7.078, p = .004, \eta^2 = .261$
•			•	$F(5,100) = 9.355, p = .001, \eta^2 = .319$
	•		•	$F(5,100) = 6.601, p = .006, \eta^2 = .248$

The threshold for reporting results was  $p \leq .010$ . For Intensity, no results are reported as none of them exceeded the threshold

account. In each of these three cases, roughly 30% of the variance in the data could be explained.

### 6.4 The valence–arousal (VA) model versus basic emotions

When both emotion representations are compared, the following ten main conclusions can be drawn:

- Both emotion representations can handle the variation in participants, even without including additional information such as the environment, personality traits, and gender; see Tables 3, 4, 5, and 6.
- Using the VA model, a very high amount of variance can be explained: 90%. This is much higher than with the basic emotions: 18% (cf. Tables 3 and 5).
- With the VA model compared to the basic emotions as representation for emotions, a multiple of the effect was found (cf. Tables 3, 5 and 4, 6).
- The SD F0 showed to have a good predictive power with both emotion representations; see Tables 4 and 6.
- The intensity of speech ( $\mathcal{I}$ ) is by far the most informative feature for the VA model; see Table 4. In contrast, with the basic emotions, it has no predictive power at all; see Table 6.
- The energy of speech ( $\mathcal{E}$ ) was a very good predictive power for arousal and a good predictive power for the six basic emotions; see Tables 4 and 6.
- The ECG feature HRV showed to be heavily influenced by multiple factors that were included in the analysis. However, when these are taken into account, HRV can serve as a rich source of information; see Tables 4 and 6.
- The personality trait extroversion had no significant influence on the participants' experience of emotions; see Tables 3, 4, 5 and 6.

**Table 5** Results on the repeated measures MANOVA on the six basic emotions

E	P <sub>N</sub>	P <sub>E</sub>	G	Specification of effect
				$F(20,400) = 4.330, p < .001, \eta^2 = .179$
•				$F(20,400) = 2.332, p = .001, \eta^2 = .106$
	•			$F(20,400) = 4.777, p < .001, \eta^2 = .194$
•	•			$F(20,400) = 4.710, p < .001, \eta^2 = .191$
•			•	$F(20,400) = 4.869, p < .001, \eta^2 = .196$
	•		•	$F(20,400) = 3.951, p < .001, \eta^2 = .166$

The threshold for reporting results was  $p \leq .010$

- Gender has some influence, although limited; see Tables 4 and 6. For the speech signal, this could be partly explained by the normalization of the signal.
- Although approached from another angle, both emotion representations as treated in this article share many characteristics. This is mainly because a discrete representation of the VA model was used that can distinguish six compounds, similar to the six basic emotions.

As is illustrated by the current study, the representation of emotions remains a topic of debate; see also Sects. 2 and 3. In practice, both discrete basic emotions and dimensional models are applied [18, 27, 33, 66]. This study compared these two representations. Data of the current study suggest that the VA model is most appropriate, as the explained variance is much higher than with the basic emotions: 90% versus 18%. As Eerola and Vuoskoski [27] state, the resolution of the discrete and categorical models is poorer. Moreover, current results suggest that there is no such thing as a basic emotion (cf. [33]). The discrepancy in explained variance of the present analyses (see Tables 3, 4, 5, 6) can be attributed to the variance of the stimuli within one category of one basic emotion.

With both models of emotion, many interaction effects have been reported in the accompanying sections, in particular in relation to HRV. However, even twice as many effects would have been reported if a less sharp, more loose threshold for reporting results had been taken; for example,  $p \leq .050$ . More than anything else, this illustrates the complexity of people and their emotional state. Moreover, more than a choice for one of both emotion models, the current data suggest that a holistic model would be most appropriate. This also explains the variation in results reported in the literature, in particular in research that goes from laboratory to life [99]. Despite its drawbacks, studies that aim to bridge this gap and take into account multiple factors should be encouraged. With the current study, such an attempt has been made; however, as the data illustrate, many more are needed.

## 7 Discussion

This section will discuss the results presented in the previous section further and relate them to the current state-of-the-art research. As was described in the introduction (Sect. 1), this research features five key issues, namely: (1) hybrid (i.e., speech + biosignals) affective computing, (2) modeling emotion, (3) including environment (or context), (4) taking people's personality into account, and (5) unveiling the possible importance of demographic information. Each of these key issues will be discussed in this section.

Next, a brief general discussion will be provided. We will end this article with some conclusions.

### 7.1 The five issues under investigation

Nowadays, not only speech and computer vision but also biosignals such as ECG can be applied completely unobtrusively [2, 23, 37, 58, 64, 75, 77, 106, 110]. Speech and biosignals are par excellence suitable for personalized and ubiquitous emotion-aware computing technology. However, surprisingly, this combination has hardly been explored; except for the author's own work [97], the only work the author is acquainted with that applied this combination is that of Kim et al. [41, 42, 44, 45]. Processing both signals in parallel can, however, be done conveniently, as is illustrated by this study; see also Fig. 2, and provides a potentially rich source of complementary information. This was confirmed by the analyses presented in the previous section; see also Tables 3, 4, 5 and 6. True bimodal (or hybrid) including biosignals and either speech or vision-based techniques should be explored more often, despite the various methodological and technical hurdles that need to be taken for its execution. Moreover, without any doubt, trimodal (i.e., biosignals, speech, and vision-based) affective computing would also be fruitful.

To ensure the correct assessment of the experienced emotions of people, the IAPS set was used in the current research [18, 52, 66]. Throughout the years, IAPS has become a ground truth for emotion research, as it is repeatedly well validated. Since the representation of emotions is still a topic of debate, both the dimensional VA model and the categorical basic emotions were employed, using the same set of IAPS pictures [52, 66]. This enabled a one-on-one comparison between both emotion representations [18, 27, 33, 66, 84]. Although the various representations of emotions are frequently discussed, it is rare that two (or more) models are mapped upon affective signals (cf. [97]). However, par excellence, the setup of the current research facilitated this. The results, as discussed in the previous section, support both models. However, more convincing effects have been found for the dimensional VA model. Although further studies should be conducted on the mapping of affective computing techniques upon models of emotion, the results of the current study provide a clear indication.

That context plays its role in human functioning (e.g., information processing) is generally accepted. However, how to operationalize such an abstract concept? Moreover, is context not different for us all (e.g., because it depends on our memories)? To enable a feasible operationalization of the concept context, it was brought down to the concept environment. The same study was conducted in two environments. Half of the participants participated in a living-

room setting and half of them participated in an office setting. This enabled a comparison between both settings. Both repeated measures MANOVAs (see Tables 3, 5) showed a (very) sharp decline in power and explained variance when environment was taken into account as a factor. This implies that including environment as a factor introduces noise instead of an additional source of information that can explain the variance in the data. However, the (univariate) ANOVAs, with both emotion representations (a separate one for each of the four features), provide another point of view. With these analyses, environment did help to unveil emotions. This suggests that the combination of features chosen for this study can handle the influence of the environment (or context) excellently. This stresses the complementary characteristics of the features chosen, as was already claimed earlier on in this article. In parallel, it identifies the influence environments do have on physiological responses to emotions. Follow-up research should explore this intriguing finding further.

The personality traits neuroticism and extroversion, both known to influence the experience of emotions [21, 62, 65, 67, 97], were assessed to determine their relation to the affective state of the participants. Independent of the emotion representation chosen, the personality trait extroversion has shown to be of hardly any influence. This is in line with an earlier study by the author [97], but deviates from other literature [21, 62, 65]. In contrast, the personality trait neuroticism has shown to be of influence, with both emotion representations. However, its influence depended heavily on the emotion representation chosen. With the dimensional VA model, the repeated measures MANOVA (see Table 3) showed a (very) sharp decline in power and explained variance when environment was taken into account as a factor. As with the environment, this implies that including the personality trait neuroticism as a factor introduces noise instead of an additional source of information that can explain the variance in the data. In contrast, with the six basic emotions, the repeated measures MANOVA (see Table 5) showed a small increase in both power and explained variance when environment was taken into account as a factor. The (univariate) ANOVAs, of both representations (see Tables 4, 6) reveal that the personality trait neuroticism is of influence on the distinct features, however, only in combination with either the environment, gender, or both. So, personality traits seem to play their role in our emotional experiences and their reflection in our speech and ECG; however, it is a complex interplay of factors, which may be expected to be challenging to unveil.

Various demographic information were gathered on the participants, namely: level of education, age, nationality, and gender. The possible effect of these factors was assessed with preliminary analyses. These analyses have

not been reported for reasons of brevity. The preliminary analysis showed the absence of an effect due to the level of education; hence, this factor was excluded from further analysis. However, this lack of effect can be explained by the small variance in level of education between the participants. Age influenced neither the reported emotions nor the physiological signals accompanying them. This is in contrast with some of the literature that states that age is of importance [49]. This is even specifically shown for cardiovascular reactivity on psychological stress [55, 93]. This lack of effect can be explained by the skewed distribution, as well as by the limited variance of the age of the participants; see also Sect. 4. The nationality of the participants was heavily skewed towards Dutch: 26 of the 32 participants on which the analyses were conducted did have a Dutch nationality. Therefore, the choice was made to divide the participants having a Dutch and non-Dutch nationality. However, this analysis did not reveal any effect on this factor. Nationality was included as a representation of both cultural and ethnical factors. Both these factors have been reported to be of influence on physiological responses in relation to emotions [87]. More than anything else, it should be concluded that this research was not optimized for the assessment of this factor, which explains the absence of any effect. The gender of the 40 participants was perfectly balanced; so, in contrast with level of education and age, for this factor, a maximal variance was obtained. In line with the literature, gender was shown to be of effect [54, 93]. However, this effect was marginal, and additional research is needed to unveil the exact influence of gender on the relation between biosignals and speech and emotions.

## 7.2 Conclusion

The results of this study show that the three speech measures (i.e., SD F0,  $\mathcal{I}$  and  $\mathcal{E}$ ) in combination with only HRV already provide a reliable, robust, and unobtrusive method to reflect user's affective state. Of course, many more features could be derived from both the speech signal [29, 86, 92, 105, 109] and the ECG [3, 15, 18, 71, 81]. However, this was not the aim of this study and also appeared to be unnecessary. The current results are already excellent with 90% explained variance for the VA model (see Sect. 6), which also challenges the claim that personalized processing of such signals is required.

The debate on how to define emotions remains intriguing, as it is so close to our everyday lives. However, for personal and ubiquitous computing technology, practical considerations should also be taken into account. The processing scheme introduced in this study enables the unobtrusive assessment of affect. In practice, this can be achieved through either sensor networks or wearable

sensors; for example, as embedded in electronic textiles [106, 110]. Both of these branches of engineering have flourished since the start of the current century. One can only conclude that this technology is rapidly maturing [2, 23, 64, 75] and, consequently, is applied in a variety of domains; for example, health monitoring [1, 23, 37, 64, 75, 106, 110]. While the underlying technology is becoming both more miniaturized and more robust [37, 64, 75], various probes have been introduced. Generic, ambulatory, wearable ECG systems [58, 77], empathic chairs [4], and digital plasters [106] have been introduced. It seems that sensor networks' and wearable sensors' main drawbacks is that of many wireless applications, such as your laptop: battery life [1, 37, 64, 106, 110].

All in all, ubiquitous computing, following AI, has to embrace emotion as an essential element in pursuing its next level of development. It is surprising that the combination of speech and biosignals has hardly been used before to unveil people's emotions. Par excellence, this combination of signals has been shown to be suitable for unobtrusive emotion recognition. This having been said, the current study provides a significant leap forward in bringing personal ubiquitous emotion-aware computing to practice.

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