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# Using the Internet of Things to Support Emotional Health

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## Abstract

A first step towards emotional well-being is to monitor, understand and reflect upon one's feelings and emotions. A number of personal emotion-tracking applications are available today. In this paper we describe an examination of these applications which indicates that many of the applications do not provide sufficient support for monitoring a full spectrum of emotional data or for analysing or using the data that is provided. To design applications that better support emotional well-being, the full capabilities of the Internet of Things should be utilized. The paper concludes with a description of how Internet of Things technologies can enable the development of systems that can more accurately capture emotional data and support personal learning in the area of emotional health.

**Keywords:** emotion, emotion-tracking applications, Internet of Things.

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## 1. Introduction

Very little research has been conducted on the extension of Internet of Things (IOT) systems [1] to include emotion detection. Similar to how wearable health tracking devices connected to the IOT can track physical metrics such as steps and heart rate for personal use or in a healthcare context [2] [3], data relating to emotions can also be tracked using wearable devices, mobile applications, smart objects or spaces, and other sensors as part of the IOT.

Emotions influence health both directly (through physiological responses) and indirectly through changes in decisions and behaviour [4] [5]. Although the majority of studies on emotions and health have been focused on cardiovascular disease, indicating that individuals who can better regulate emotions are at a significantly lowered risk for heart disease [6], there is growing recognition of a more general relationship between emotions and health [7].

Emotions are complex states, which have neurological, physiological, cognitive, and behavioural aspects [8]. Regarding the terminology to be used, "emotion" refers to a strong physical and mental response, deriving from a particular stimulus (person, situation or event), which is generalized and occupies the person as a whole for a short period of time [9]. Although sometimes they are used interchangeably, it is important to consider the difference between the terms of "emotion" and others such as "affect", "feeling", or "mood", which are different in degree of consciousness, duration, and distinctiveness ability [10].

Nowadays, IOT has become more complex in terms of user experience [11], human computer interaction, and design process requirements [3] [1]. In this context emotion-tracking allows designers and developers to create products and services with better interfaces and more suited to the user's needs [12] [13]. It may be useful for improving healthcare services, making them more personalized, inclusive, and especially, more useful for the monitoring, diagnosis and treatment of cognitive and psychiatric diseases [14] [15].

Emotion-detecting measurements have been developed by relating emotions with indirect measurements such as human behaviour (voice patterns, facial expressions, movement, etc.), or biometric signals (physiological sensors (ECG), brain wave sensors (EEG), etc.). While acknowledging the complex nature of emotion, some researchers believe that the best way to determine what an individual experiencing an emotion actually feels is to use self-reporting [16]. That approach is what we see in the personal emotion tracking applications available today.

To understand how personal tracking of emotions is currently enabled and how the results are used, we examined consumer-focused, personal emotion-tracking applications. To structure the evaluation, a framework developed to compare personal informatics applications was used [17]. Following this assessment of the current state of emotion-tracking applications, we summarize selected literature about how to measure emotions, and we discuss additional considerations that should be addressed in the design of IOT systems that address emotional well-being. The paper concludes with a discussion of implications for the design and development of emotion-sensing IOT systems and identification of areas that are particularly in need of additional research.

## 2. Analysis of Self-Reporting Emotion Apps

To explore existing consumer applications that support self-reporting of emotions, keywords "happiness", "emotions", "mood", "mood tracker", and "feelings" were used to search for apps on Google Play and the App Store. In addition, we searched forums on the internet where various types of emotion apps were discussed. The selection criteria was for the application to have as its primary function the ability to track and individually reflect on emotions. (This excluded, for example, applications used to track mood as a way of predicting menstrual cycles.)

The search resulted in 92 apps of which 35 were disregarded because they did not work, required the login associated with a therapy group, turned out not to have emotion tracking as a primary task or were no longer available. One application (EMet) works with a separate hardware sensor (galvanic skin response) but the sensor is no longer available for purchase so the app was therefore not included in the analysis. (A complete list of the applications can be obtained from the authors.) It is interesting to note that very few (only about 30%) of the developers of the applications in this study claim to be grounded in psychological research or practice.

The remaining 57 apps were installed and analysed according to Ohlin et al.'s [17] classification system which includes a total of nine dimensions on which to evaluate the applications: (1) selection of data to collect, (2) temporality of collection, (3) support during manual entry, (4) data collection control, (5) form of goal setting, (6) data analysis control, (7) form of comparison, (8) subject(s) of comparison and (9) appraisal.

We have grouped these dimensions based on the type of support provided to the user, and this more parsimonious structure will be used to frame our evaluation of emotion-tracking applications. Collection support deals with how to support the user in terms of collecting data (dimensions 1-4), which includes what data to record, when and how often to do so, and assistance provided in the data collection. Procedural support is about how the app supports users in their daily use of the app such as by providing notifications that it is time to record data and by providing encouragement and other types of feedback (dimensions 4-5). Analysis support includes features such as allowing or assisting the user in setting goals. The third type of support, analysis support, is about how the users can be supported when analysing and reflecting on the data (dimension 6-9). This could include tracking progress towards achieving goals and determining how the results will be compared to the user's past results and/or to others. These are summarized in Figure 1 and described in more detail below.

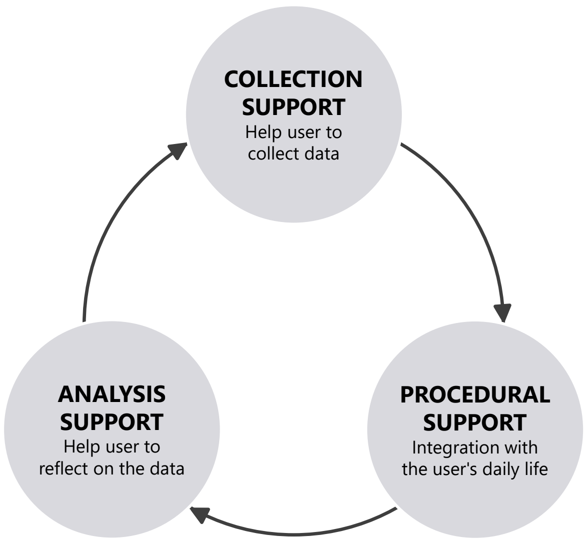


**Figure 1.** Type of support that apps provide for emotion-tracking applications. Based on Ohlin et al.'s [17] classification system.

### 2.1. Collection Support

Collection support refers to how data is collected and how the collection is made easier for the users. In most of the apps there are predefined emotions to choose from in the form of symbols and/or words. In some of the apps it is possible to make a selection from a subset of emotions to use for reporting. Half of the apps also allow for user-defined data by adding free text to describe a feeling. A few apps allow for more customization, for example T2 Mood tracker and InFlow.

As mentioned, only one of the apps found in the original search, EMet – emotional meter, has support for hardware sensors that collect emotional data (via galvanic skin response) continuously. However, this sensor is no longer available so the application was not included in the analysis. All the other apps collect emotion data through periodic data entries by the users. Only one quarter of the apps analysed allow the user to edit a previous entry.

To represent emotions most of the apps use emoji of different kinds. A couple of the apps use an affect grid [18] where the user position’s his or her emotion in one of four quadrants depending on whether the user feels a pleasant or unpleasant feeling in combination with high or low arousal.

Because the apps rely solely on self-reporting, the users need to be reminded to record an emotion. Surprisingly, fewer than half of the apps contains some kind of notification. How the user is notified or prompted varies. Most of the reminders are simple notifications in the mobile phone’s notification field. Some apps use widgets that are activated and prompt the users to record their emotions when opening the phone. It is in many cases possible to tailor when the notification should show up. Only four apps use random notifications.

What we can learn from the analysis of the apps in terms of data collection support is that it is important to represent emotions in a way the individual user finds appropriate. The representation must be nuanced and reflect the user’s experienced emotion. A customizable combination of words and symbols might be a good way to move forward. Another aspect to consider is how the representation of the emotions may evolve in line with the user’s understanding of their own emotions.

### 2.2. Procedural Support

Procedural support assists in the daily use of the application, aiding in integrating the application with the user’s lifestyle and achieving desired outcomes. In their evaluation of general apps for personal informatics (PI), Ohlin et al. [17] identified procedural support as generally underdeveloped. The same can be said for emotion-tracking apps. There are only a few attempts to combine activities with emotion tracking. For example, Activity Mood Tracker makes the user track her emotion before and after a pleasant activity to make the user reflect on the potential change.

Goal setting is considered important in PI, but in the emotion apps goals are sparsely considered. Moodlytics makes an attempt by letting the user choose a goal for how long she wants to be happy every day. This kind of goal is very crude in the context of emotions where it could potentially lead to a more negative state if the goal is not achieved.

When it comes to data analysis control none of the apps try to prompt the user to look back at the reported values. It is completely up to the user if and when to reflect on the reported emotions.

Rather than setting goals as quantifiable measures, there may be better ways to direct emotion-related activities such as through describing an overall ambition or desired state. The notifications that exist in the reviewed apps are rather blunt. A more context-aware approach to providing notifications should be considered. In addition, the users should be prompted to reflect on the day to be able to learn what made them feel like they did.

### 2.3. Analysis Support

Analysis support is neglected in most of the apps. The apps display the data in different ways and in different historical time spans or in calendars, but there is not any support to interpret the data and guide the user as to what the data may mean. As mentioned above, Emotion Sense interprets a set of questions and presents it as insight of who you are, but there is no transparency of how this is done which both leads to a lack of trust and prevents learning from it.

It is common in personal analytics to compare the results with self and others. In emotion apps it is mainly oneself that is the subject of comparison. An exception is Emotion Sense. In Emotion Sense the user has to answer a set of questions that are evaluated and compared to statistics about the general population.

Sharing data with friends or therapists is quite common in these emotion-tracking applications. This can be done in different ways and with different mediums such as e-mail, Twitter, Facebook etc. Most of the interaction and appraisal take place outside of the app. MoodPanda has taken another direction and has an internal forum where users can respond to other users’ emotions and give them a virtual hug.

The take away regarding analysis support is that there is a need to visualize a bigger picture where the user’s emotions are put in context, possibly by comparing with other users in a clever, non-critical way. There is also a need to help the user interpret the data. The ability to share the data, if desired, to receive social support is another important aspect of these applications.

## 3. Measuring Emotions

Measuring emotion, involves assessing the conscious or unconscious responses we have to them; there are two dominant approaches to classify emotions: the basic emotions and dimensional approaches. Although there is no consensus about their number or nature, the so-called basic emotions are commonly assumed to be: anger, happiness, fear, sadness, surprise, disgust and love, anticipation, joy and trust [9]. The dimensional approach identifies the characteristics that allow us to differentiate between the different emotions. Some of the dimensions are the following: arousal (deactivating or activating), valence (negative or positive), intensity (low or intense), duration (short or long), frequency of its occurrence (seldom or frequent) and time (retrospective like relief, actual like enjoyment, prospective like hope) [10]. These two approaches are represented and related in the two-dimension “circumplex model of affect” [19], which has been used as a fundamental emotional model for many applications. Below we summarize the main techniques to measure emotions, extracted from reviews about the field.

### 3.1. Self-Reporting Tools

As has been seen in the analysed applications, self-reporting tools are the most used. They are based on measuring the psychological dimension of emotions, through explicit and subjective description by the subject. Authors distinguish between two types of self-reporting tools, verbal and non-verbal [9] [10] [14] [20] [21], which is aligned with the commercial applications observed.

(i) Verbal Self-Reporting. Subjects report on their emotions in an explicit way, with the use of questionnaires that can be answered by text or voice, and with predefined, or open-ended questions and scales. Some examples are the Academic Emotions Questionnaire (AEQ) [22], Semantic Differential Scale [23], Positive and Negative Affect Schedule (PANAS) [24], or Affect Grid [18]. Tools used to measure emotional intelligence, such as the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT) [25], or the Social and Emotional Learning (SEL) [26] could also be included in this classification.

(ii) Non-Verbal Self-Reporting. It includes language-independent tools that can be used in different cultures, like cartoons, or emoticons which represent the emotion the user is feeling and can be easily selected by the user. Some examples are the Self-Assessment Manikin (SAM) [27], PrEmo [20], or Emoticons Experience Sampling Method [28].

### 3.2. Use of Biosensors

As with the Self-Reporting tools, biosensors try to measure psychological responses [14], but in this case with objective measurements. This is also called biometric measurement of human emotions [13]. Most of these measures are based on recordings of electrical signals produced by the brain, heart, muscles, and electro-dermal analysis [9] [10]. Biosensors are usually integrated into portable devices, smartphones, and mainly in wearable sensors or even embedded in clothing [15]. In the near future, it will be also possible to collect much more information with smart implants or ingestible sensors swallowed as pills [29]. Some examples of technology currently used for emotion-tracking proposes are the following [9]:

- Electromyogram (EMG): muscle activity.
- Electroencephalography (EEG): brain activity.
- Electrodermal Activity (EDA), Skin Conductance (SC) and Galvanic Skin Response (GSR): hydration in the epidermis.
- Electrocardiogram (EKG or ECG): heart activity.
- Electrooculogram (EOG): size and movement of eyes.
- Blood Volume Pulse (BVP): blood pressure.
- Respiration: rate and the depth of breath.

### 3.3. Observation of the User’s Behaviour and Environment

These techniques attempt to identify the individual’s emotional state by observing their externalized reactions and their physical responses [14] [9]. Observation techniques aim to detect patterns in the actions individuals perform in their daily lives and relate them to the emotions experienced. For this, information is collected either from sensors placed in the environment, (home objects and devices) or from devices and space usage patterns [15]. With them, it is possible to carry out processes of activity recognition, context measurements, and social relations objectification.

Some of the most common techniques are metadata analysis of smart devices, facial expression analysis [30] [31], voice modulation/intonation (speech) analysis, or body and/or hands motion capture (gestural recognition). Relating to the last point, there are some studies that have created databases that relate emotions with gestures performed by actors [32] [33] [34] [35].

## 4. Additional Considerations for Emotion-Sensing Apps

The same types of metrics, tracking, and support structures cannot be taken directly from personal informatics applications and applied without modification to emotion tracking applications. There are several significant differences between ‘emotion management’ and typical personal informatics (also called quantified self) applications. Four of these – levels of abstraction, measurement technique selection, ethical issues, and goal setting – are discussed below.

### 4.1. Levels of Abstraction in Measuring Emotion

As has been observed in the compilation of techniques to measure emotions, when evaluating emotion, we are not attempting to capture just one measurable physiological state such as heart rate or one value captured by sensors on a device. Emotion involves a range of responses from the neurobiological to the behavioural. The context and other factors specific to the individual may influence the subjective feeling of the emotion experienced. Thus an individual's emotional state at any particular moment reflects and is influenced by a broad range of factors. To truly capture an emotional state, it may be necessary to combine neurological, physiological, and contextual data on an on-going basis. Environmental factors such as traffic, temperature and noise level may contribute to an individual's emotional state. Location of the user, the proximity of others, and life events and activities may influence emotion. A simple periodic self-reporting of emotional state may be useful in tracking how the user feels over time, but does not address the deeper issues of contributing factors. It may be necessary to measure contributing factors as well as emotional state to provide a complete picture and determine appropriate actions to take to rectify a problem or make a change in order to improve overall health.

## 4.2. Measurement Technique Selection

One of the main challenges for the future is to discover which are the most appropriate factors to measure, as well as the best tools for this purpose. Nowadays, there is not a universally accepted rule to determine which method is most suitable. Measurements have to be in context, and done in parallel with the task without being disruptive [9]. The selection should be made, from the perspectives of predictive quality, non-intrusiveness, as well as other challenges that are described below such as privacy or ethical issues.

According to the literature, non-verbal self-reporting constitutes a more user-friendly way than verbal techniques [9] [20] [28]. Wearable biosensors are designed mostly for lab experiments, so they are usually invasive and cumbersome, although neuroscience has proven that they are useful tools to detect negative emotions (e.g. stress or fear) [9]. Finally, it is considered that the observation techniques can adapt more easily to our daily life [14].

In order to select the best techniques, we need to integrate data generated by users, their environments, sensors and other devices and sources. In this way, methods to measure and predict emotions by combining self-reporting and objective measurement could be achieved as a first step [21]. A small example of a database along these lines is represented in Figure 2.

| ENVRONMENT | HUMAN BEHAVIOR | | BIOMETRIC SIGNALS | |
|---|---|---|---|---|
| Noise (dB) | Number of messages | Steps | Heart rate (bpm) | Self-reporting |
| 70 | 15 | 5020 | 90 | Stressed |
| 45 | 160 | 4032 | 86 | Satisfied |
| ... | ... | ... | ... | ... |

**Figure 2.** Database example of multiple measures related to emotional state (Non-real data).

## 4.3. Privacy and Ethical Issues in Measuring Emotion

There are many challenges facing the development of emotion-tracking applications using IOT including scalability (due to the potential for massive volumes of data), miss-labelling and integrity of data, clinical utility, lack of generality, battery life, intrusiveness, user experience, context awareness, security, privacy, and ethical and societal issues in medical and non-medical applications [14] [15].

We view privacy and ethical issues to be among the most critical. In particular while there are certainly privacy issues surrounding the capture and use of typical personal informatics data such as location and activity level, the risk to the individual is potentially much greater when we consider capturing data regarding emotional state. One area of concern is the ability of marketers to target potential customers at a deeply personal and more vulnerable level. The risk of miss-use of emotion data to manipulate actions seems to be greater than with other personal tracking metrics.

## 4.4. Goal Setting for Emotions

Another significant difference between personal informatics health tracking systems and emotion tracking systems is in the area of goal setting. If an individual wants to lose weight, for example, it is relatively easy to monitor the two primary components: input of calories and amount of exercise. If an individual wants to be happier, it is not clear that there are general quantifiable goals that can be tracked to help meet this objective. A more context-specific and personalized strategy is needed in order to support the user to achieve her/his objectives.

It is likely that the strategies necessary to achieve desired changes in emotion [4] will be more complex than those needed to change more straightforward health behaviours. Transparency in thoroughly explaining any decisions regarding recommendations is essential to establish the level of trust that would support such major initiatives.

# 4. Conclusion

This paper has provided a high-level overview of emotion tracking applications and summarizes the main technologies that support emotion tracking. Our examination provides a baseline from which to move forward in designing applications that support health through self-tracking of emotions. While there are useful features in some of these apps, such as the ability to customize the particular data that is recorded and to reach out to social networks, much more functionality is needed and is in fact possible with today's IOT technology. Today there are sensors that can measure biological and neurological responses and states continuously, and these can become part of future IOT emotion-management systems. Via our context-aware IOT networks we can collect data on a broad array of environmental factors that may influence stress, emotions, and the ability to respond to them which will allow us to design applications that can be not only context-aware but also emotion-aware.

Additional research is needed to determine the appropriateness of goal setting in the area of emotional health, and perhaps to find other means to support individuals who are striving to change their emotional state or response. In addition, tools will be needed to support the tracking and reporting of emotion data to aid users in the appropriate interpretation of the data and to create self-learning environments where not only can users measure their emotional states, but can also determine the best individualized means to achieve positive results.

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