# Heart Rate-Based Emotion Recognition and Adaptive Emotion Regulation Support with Wrist-Worn Wearables: A Systematic Literature Review

**Elias Müller, Ivo Benke, and Alexander Maedche**

**Abstract** Emotion regulation (ER) is a key skill since emotions play an essential role in personal development and in understanding social interaction. However, ER is unequally developed in humans and many are searching for ways to improve it. Neuro-adaptive systems bear a large potential for support in this endeavour with adaptive ER support based on biosignal. With the widespread use of wrist-worn wearables, new opportunities are emerging to capture biosignals, such as heart rate (HR), from the wearer in everyday life. This opens up the potential to use wrist-worn wearables to provide adaptive ER support. In this paper, we present a systematic literature review to provide an overview of the state-of-the-art in research on HR-based adaptive ER support with wrist-worn wearables. Specifically, we focus on the interplay between emotion recognition, wrist-worn wearables and adaptive ER support. Our findings show that HR-based wrist-worn wearable systems equally intervene via forms of feedback and external regulation by others and only four studies actually adapt the system. Further, many studies focus on response-based regulation or situation modification or selection strategies. To further research, we see research gaps in the ease of application of technical implementation, including biosignal processing and the use of ER support in systems.

**Keywords** Emotion recognition · Emotion regulation · NeuroIS · Biosignals · Adaptive systems

E. Müller (✉) · I. Benke · A. Maedche
Karlsruhe Institute of Technology (KIT), Kaiserstr. 89, 76133 Karlsruhe, Germany
e-mail: elias.mueller@kit.edu

I. Benke
e-mail: ivo.benke@kit.edu

A. Maedche
e-mail: alexander.maedche@kit.edu

# 1 Introduction

Emotion regulation (ER) is a key skill for humans since emotions play an essential role in personal development and in understanding social interaction [1, 2]. For example, emotions allow humans to assess specific situations, foster or hinder learning processes and memorize information [3]. Consequently, ER plays a central role in the development of transferable skills such as empathy, leadership, or self-empowerment [4]. ER refers to the things we do to influence [4] which emotions we have, when we have them, and how we experience and express them [5]. It is executed via the application of dedicated ER strategies [6, 7]. Consequently, the application of ER strategies is a key skill for developing transferable skills and for going through life successfully in general. However, ER is unequally developed in people and many are searching for ways to improve it and related skills as evidenced by the multitude of courses on personal development, e.g., in mindfulness, leadership, or empathy. In this paper, we take a look at the perspective on how to leverage sensor technologies embedded in wearables that support recognizing emotions via biosignals for ER support in the field. A promising electrical biosignal to understand emotions leverages electrocardiogram (ECG) to compute heart rate variability (HRV) [8]. Today, commercially available, affordable wearable devices provide the ability to capture cardiovascular activity. Specifically, smartwatches [9] as well as other wrist-worn wearables are becoming widely used in the population. According to Parks Associates, in 2021 22% of American households own a smartwatch which is most commonly used for activity, health and fitness tracking [10]. As wrist-worn wearables are equipped with sensors that provide increasingly accurate readings, the popularity of emotion-recognition smartwatches has also increased for research [11]. Although the sensor accuracy does not match other wearables [12], like a chest strap, wrist-worn wearables are being used in various studies and have shown to provide valuable data for recognizing emotions. By being non-invasive, widespread and suitable for everyday use, they offer interesting possibilities for use in neuroadaptive systems, which is one of the research areas of the NeuroIS community and is expected to grow in the future [13–15]. In contrast to existing publications delivered by the NeuroIS community that focused on specific sensors and biosignals [12, 16–19], the focus of our review is the interplay between (1) emotional states derived from biosignals and (2) the NeuroIS system using wrist-worn wearables.

To obtain an overview of the possible applications of wrist-worn wearables and their possible integration into emotion-adaptive systems, we conducted a systematic literature review (SLR) to provide a consolidated view of research findings on ER support using emotion-aware smartwatches answering the following research question: *What is the state-of-the-art in research on emotion-adaptive regulation support using wrist-worn wearables with heart rate data?*

We analyzed the publications identified in our SLR through a morphological box based on a conceptual model of adaptive ER support systems which consists of the steps emotion recognition, the adaptation logic, the intervention type of the adaptive ER support system, and the ER strategy family in place (see Sect. 3). Our results show that wrist-worn wearable systems based on biosignals from the heart rate (HR) intervene to support ER via feedback and notification, through external regulation by others. Only four studies actually adapt the system. Further, many studies focus on response-based ER or situation modification or selection strategies.

## 2 Method

In our paper, we followed the SLR search process proposed by Webster and Watson [20] to categorize the various data records. First, we defined the scope of the search in form of the search string. It consists of three concepts: wrist-worn wearables, the ability to recognize and regulate emotions, and the cardiac biosignals to recognize emotions. The detailed search string was: *("smart device" OR "smartwatch" OR "smart watch" OR wrist-band OR "wrist band" OR "wrist bands" OR "wrist worn" OR "wrist-worn") AND ("emotion regulation" OR (emotio* AND regulat*) OR emotion-aware OR "emotional context" OR "affect regulation" OR affect-aware OR "affective context") AND (heart-rate OR "heart rate" OR ecg).* Second, we selected the databases ACM digital library, IEEE Xplore, AIS eLibrary, Springer Link, and Web of Science Core Collection for our search. In the databases that allowed an abstract search, this was applied to the first and second "AND" condition of the search string. Third, we included only publications published later than 2014 since corresponding wearables smartwatches are a relatively innovative technology, e.g., the Apple Watch was introduced in 2014 [21]. Another inclusion criterion was that we only looked at peer-reviewed journals and conference papers. With our search strategy, we obtained 564 results. Through manual reviewing them on the SLR objective, we received 23 results in total. In a forward-backwards, we found additional 9 publications, whereby one publication targeted the same prototype, were found. In a final step, the 31 results were analyzed according to the studies conducted and the Conceptual Model explained in Sect. 3.

## 3 Conceptual Model

We conceptualize emotion recognition and adaptive ER support based on wrist-worn wearables with a cycle consisting of four steps (see Fig. 1).

Our conceptual model distinguishes between a human and technical system perspective. From a human perspective the central trigger for adaptation is the appearance of emotions. Emotions in general can either be assessed manually (e.g., through surveys) or automatically. We follow an automated approach to discover emotions. In step (1) **emotion recognition**, sensors (in our case mostly embedded wrist-worn wearables) are leveraged, raw data processing is performed and classification algorithms are applied. Subsequently, step (2) covers the **adaptation logic**. This step builds on the detected emotion and describes the procedure how an intervention will

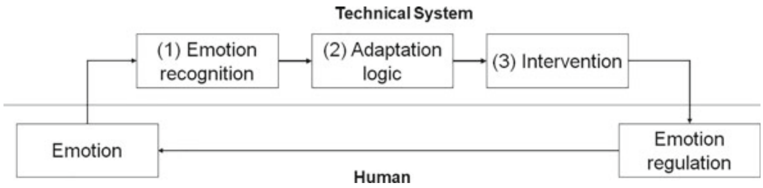


**Fig. 1** Conceptual model

be triggered based on the recognized human's emotion. Finally, step (3) **intervention** describes how the system responds to the recognized emotion and the defined adaptation logic in order to influence human behavior. These interventions can be, for example proposing exercises to be performed by the human, adjustments to an application or feedback.

Finally, again from a human perspective, **emotion regulation** describes the strategy for regulating the human's emotion during or after an intervention. Existing literature typically suggests grouping of strategies in 5 families: Situation Selection, Situation Modification, Attentional Deployment, Cognitive Change and Response Modulation [22],

## 4 Results

We present the results of our SLR in a morphological box (Fig. 2), the underlying data is captured in Table 1 in the appendix. The dimensions of the morphological box describe the study characteristic, the emotion, the steps from the technical system, and the emotion regulation.

The dimension **study characteristics** provides information on the type of investigation conducted in the studies, either for data collection (in the field and in the laboratory, 7 in total) or for the assessment of artefacts. 15 studies were conducted in a laboratory setup and 10 studies in a field setup. In 6 studies, no or other types of studies were conducted.

With regards to the **emotional model**, 13 studies followed a discrete emotional model. Five studies followed a continuous dimensional emotion model (i.e., valence-arousal), in nine studies an emotion-centric construct was classified, for example, in [23] the user's laughter was recognized. In four studies no model was reported.

The dimension of the **discrete emotion** is differentiated from the upper dimension in more detail. Anger and disgust were each chosen once as a discrete emotion, anxiety seven times, joy and surprise twice and sadness three times. Although stress is not an emotion, we added it to this dimension because the intervention for emotions is also partially applicable to stress; it was used in seven studies. Among others (5), we included related states to the discrete emotions, such as laughter [23] or engagement [24].

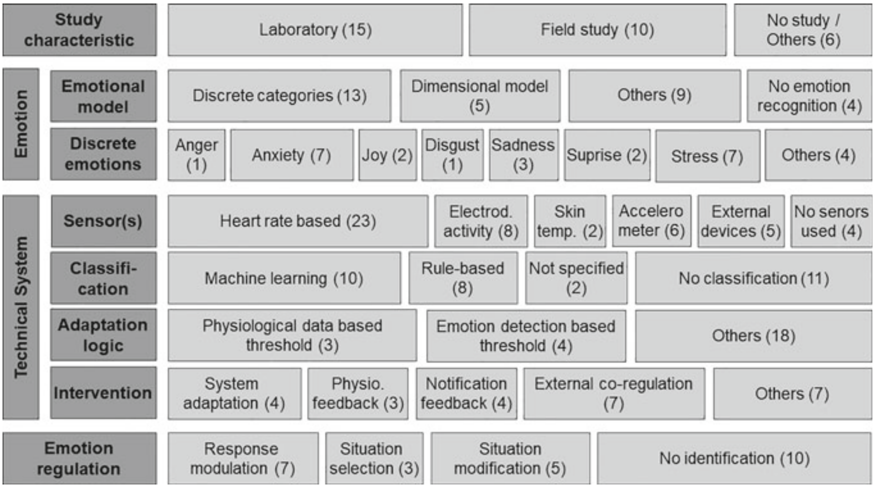


**Fig. 2** Morphological box for the SLR analysis

The dimension of **sensors** covers the various physiological sensors that have been used by wearables, mostly wrist-worn wearables, used for emotion recognition and during adaption. 23 prototypes have measured the HR. Electrodermal activity sensors were used in total of eight times. Six times the accelerator and two times the skin temperature sensor was used. In five studies, additional measuring devices were used, which recorded data that could not been measured with a wrist-worn wearable like for example, Dong et al. [25] also used a camera to capture facial expressions. Four times there was no emotion recognition, such as in CoolCraig [26]. This system focuses on behaviour and emotions in children with ADHD in a co-regulation setting.

For the **classification** of the emotion using raw sensor data, machine learning was used in ten studies, rule-based classification in eight studies, no indication was given in two studies and no emotion classification took place 11 times. This included also prototypes using emotion-related biosignals, for example HeartChat [27], which developed an HR augmented chat for emotion regulation in chats. Another example is EmotionCheck [28], which in their laboratory study evaluated the effectiveness of the intervention and the anxiety was induced by the study.

For the following analysis, we excluded all studies (6) that did not conduct the support of emotion regulation but rather focused only on recognition. We continue with those studies that represent the whole conceptual model (25).

The **adaptation logic** was based on a threshold of sensor values or features in three studies, in four studies the logic was based on the detected discrete emotion, and the remaining 18 are summarised under others. These include studies that induced the emotion or that co-regulation took place.

Different **intervention types** were leveraged: In four studies, an automatic adaptation of the system takes place, three the user received haptic rhythmic feedback on their wrist. Four times an exercise was suggested to the user by a notification. In

**Table 1** Results of the SLR

| Dimension | Characteristic | References | # |
|---|---|---|---|
| Study characteristic | Laboratory study | [23, 28–30, 32–42] | 15 |
| | Field study | [24, 27, 31, 43–49] | 10 |
| | No study | [25, 26, 50–53] | 6 |
| Sensors | Heart rate based | [23, 25, 27–37, 43–49, 51–53] | 23 |
| | Electrodermal activity | [23, 24, 29, 36, 37, 40, 42, 42] | 8 |
| | Skin temperature | [37, 52] | 2 |
| | Accelerometer | [23, 29, 38, 39, 45, 46] | 6 |
| | External device | [25, 35, 37, 46, 47] | 5 |
| | No Recognition | [26, 30, 41, 50] | 4 |
| Classification | Machine learning | [23, 25, 29, 37, 38, 40, 45, 47, 48, 52] | 10 |
| | Rule-based | [24, 32, 33, 35, 43, 44, 51, 53] | 8 |
| | Not specified | [31, 34] | 2 |
| | No classification | [26–28, 30, 36, 39, 41, 42, 46, 49, 50] | 11 |
| Emotional model | Discrete categories | [28, 31–34, 38, 42–44, 48, 51–53] | 13 |
| | Dimensional model | [25, 29, 35, 40, 47] | 5 |
| | Others | [23, 24, 27, 36, 37, 39, 45, 46, 49] | 9 |
| | No emotion recognition | [26, 30, 41, 50] | 4 |
| Discrete emotions | Anger | [34] | 1 |
| | Anxiety | [28, 31–34, 42, 52] | 7 |
| | Joy | [38, 51] | 2 |
| | Disgust | [34] | 1 |
| | Sadness | [34, 38, 51] | 3 |
| | Surprise | [34, 40] | 2 |
| | Stress | [30–32, 43, 44, 48, 51] | 7 |
| | Others | [24, 37, 44, 45] | 4 |
| Adaptation logic | Physiological data based threshold | [32, 33, 44] | 3 |

(continued)

**Table 1** (continued)

| Dimension | Characteristic | References | # |
|---|---|---|---|
| | Emotion detection based threshold | [25, 34, 41, 51] | 4 |
| | Others | [24, 26–28, 30, 31, 35, 36, 39, 40, 42, 43, 46, 48–50, 52, 53] | 18 |
| Intervention | System adaptation | [25, 32, 44, 51] | 4 |
| | Physiological feedback | [28, 33, 42] | 3 |
| | Notification feedback | [30, 31, 35, 46] | 4 |
| | External co-regulation | [24, 27, 36, 39, 40, 49, 53] | 7 |
| | Others | [26, 34, 41, 43, 48, 50, 52] | 7 |
| Emotion regulation | Response modulation | [28, 31–33, 35, 41, 42] | 7 |
| | Situation selection | [25, 43, 51] | 3 |
| | Situation modification | [24, 30, 36, 39, 44] | 5 |
| | No identification | [26, 27, 34, 40, 46, 48–50, 52, 53] | 10 |

seven studies, adaptation took place through external co-regulation and seven were categorised under other.

Finally, the distribution among the **emotion regulation** strategy families were the following: The response modulation family was used in seven studies, the situation selection in three studies and the situation change strategy family in five studies. In ten studies we could not make an allocation.

## 5 Discussion

In this study we conducted a SLR to provide an overview of research on HR-based adaptive ER support with wrist-worn wearables. Based on the results of our SLR we identified two main streams in previous research.

First, the results show that 80% of the studies conduct and investigate ER support, while the other studies focused on emotion recognition using wrist-worn wearables. These studies represent the first stream. In this stream emotion recognition is mostly conducted in a multimodal approach with multiple sensors, post-processing, and classification with machine learning. Many of these studies applied a two-dimensional valence-arousal model to understand emotions. EmotionSence [29] is an example from this stream. In a lab study, they took data from different users in different activity states, such as sitting and walking, and built different models to detect emotions in a 2D model.

The second stream includes all studies that supported ER and included either an adaptation or an intervention. Mostly the focus was on evaluating the regulation intervention or adaptation concept and not emotion recognition, which was partly induced by the study and not automatically performed. Many of the prototypes in these studies were based on the discrete or categorical emotion models, of these a lot focused on negative emotions like anxiety, anger, or stress. The adaptation logic in these studies was quite different. About one fifth of the studies gave general feedback in the form of a message to users to recommend an exercise, like FOQUS [30], which includes a feature that helps to be focused by applying the Pomodoro time management technique [31].

Four studies adapted the interaction with or the presentation of the system by adjusting the speed of interaction or adaption of the system interface. In seven studies a special form of intervention was chosen in which the emotional state or physiological data was communicated to a co-regulator who then decided whether to change the mode of communication or recommended an exercise. In three studies, the user receives artificial, heartbeat-like rhythmic feedback on the wrist to subtly calm and regulate their HR. Finally, when looking at the ER strategies applied in the studies, three groups stand out. Seven studies focused on a response-based approach by elicitation of response modulation in the participants. For example, Di Lascio et al. [23] have developed a system called *FishBuddy* that detects stress and anxiety in learners during an exercise and interrupts the learning process to regulate the emotion by using a simulated fish whose swimming rhythm reduces the HR. Second, five studies regulated emotions by modifying the situation, and three started even earlier in the ER model by supporting the application of situations selection strategies. Other emotion strategies were not applied in the sample. A reason for this might be since the ER strategy attention deployment and cognitive change require a deeper understanding of the situation and the context in order to support ER through a neuro-adaptive system.

## *Limitations and Future Research*

Although we followed a rigorous search approach our work comes with limitations. We had to make decisions with regards to the databases searched, the exclusion and inclusion criteria, and the analysis levels. We will address these aspects in future cycles. Based on our results and limitations, we have discovered potential for future research. Despite the prevalence of wrist-worn wearables in the population, we see a research gap in the area of adaptive ER support systems with an integration of all steps of our conceptual model such as adaptation logic, intervention, and regulation. Second, only three of the five ER strategy families are investigated in the studies.

To address these gaps, we see the potential for further research to bring together the technical implementation and processing of biosignals and ER support strategies and their use cases. This requires (1) methodological contributions that conceptually describe the interplay of emotion recognition, logic and intervention. Furthermore, we believe that a toolkit supporting the different steps of emotion recognition and adaptation through standardized software modules could be beneficial. This would make it possible to prototype ER support applications based on wrist-worn wearables for researchers from non-technical disciplines.

## Appendix

See Table 1.

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