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From the Inside Out: A Literature Review on Possibilities of Mobile Emotion Measurement and Recognition

MICHAEL MEYER, PATRICK HELMHOLZ, MARCUS RUPPRECHT, JACQUELINE SEEMANN, TOBIAS TÖNNISHOFF & SUSANNE ROBRA-BISSANTZ

Abstract Information systems are becoming increasingly intelligent and emotion artificial intelligence is an important component for the future. Therefore, the measurement and recognition of emotions is necessary and crucial. This paper presents a state of the art in the research field of mobile emotion measurement and recognition. The aim of this structured literature analysis using the PRISMA statement is to collect and classify the relevant literature and to provide an overview of the current status of mobile emotion recording and its future trends. A total of 59 articles were identified in the relevant literature databases, which can be divided into four main categories of emotion measurement. There was an increase of publications over the years in all four categories, but with a particularly strong increase in the areas of optical and vital-data-based recording. Over time, both the speed as well as the accuracy of the measurement has improved considerably in all four categories.

Keywords: • Emotion • Recognition • Measurement • Mobile • Digital Transformation •

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1 Introduction

The digital transformation has been on everyone's lips for quite some time. It shows itself as a technological and societally process of change and affects nearly every aspect of everyday life. At the core of this transformation lies the transition from analogue to digital, from offline channels to online channels and the change of the real world to a virtual one. Broadband Internet and the prevalence of mobile devices as well as new digital products and services are pushing the digital transformation forward. This digital transformation is also linked to create new values to improve the relationship with the user (Amit & Zott, 2001; Hagberg, Sundstrom, & Egels-Zandén, 2016). Smartphones and newer wearables in particular offer new service possibilities and trend to change the users' behaviour as they are able to access the Internet anytime and anywhere (Blázquez, 2014). Because intelligent mobile devices are equipped with many different sensors, capable of measuring the user's situation, they can provide better and more personalized digital advice in the form of user-specific and situational information (Härtfelder & Winkelmann, 2016; Rohm & Sultan, 2006).

Especially inner states like emotions can provide good insights into the user's situation and thus into their needs (Brave & Nass, 2003). The technological progress, the cost and size reduction of hardware and the further development of sensors offer more and more possibilities for situation-oriented applications (Yurur et al., 2016). By now, some devices are even able to measure biofeedback and draw conclusions about the user's emotional state (Bachmann et al., 2015; Likamwa, Liu, Lane, & Zhong, 2013; Muaremi, Arnrich, & Tröster, 2013). Emotions are very important for human beings as they influence many aspects of their everyday life (Brave & Nass, 2003; Picard & Klein, 2002). An emotion-aware information system (IS) may therefore be capable of enhancing the communication with the user while increasing the user experience (Hussain, Peter, & Bieber, 2009; Peter & Urban, 2012).

As society and user expectations change, the adaptation of IS becomes more crucial. For IS and its underlying services, it is essential not only to be able to analyse and interpret user input, but also to react emphatically to the user's emotions (Frijda, 1993; Peter & Urban, 2012). Gartner predicts that by 2022 10% of personal devices will have emotional artificial intelligence capabilities, either on-device or via cloud services, compared to less than 1% in 2018 (Gartner, 2018a).

2 Research Goal

Since emotions are triggered by situations, smart mobile devices allow to support the user in these situations (Cabanac, 2002; Geven, Tscheligi, & Noldus, 2009). The research field of mobile emotion measurement is currently difficult to oversee due to the lack of standards and the numerous possibilities of the measurement (Geven et al., 2009). To create an overview and to present a state of the art of the current research by finding suitable categories of emotion measurement as well as applications is the subject of this systematic literature research. The underlying research question of this paper is: "How can emotions be measured in a mobile way?".

Human emotions are reflected in the human body in many ways. Depending on the current emotional state, facial expressions, gestures, speech or the heartbeat change, mostly in combination with each other (Hussain et al., 2009).

These changes must first be objectively depicted with the help of technology and thus made visible to the computer (Weerasinghe, Ranaweera, Amarakeerthi, & Cohen, 2010). Since a conventional information system is not able to recognize feelings through facial expressions, gestures or bio signals, additional hardware in the form of smartphones, smartwatches or other sensor equipment as well as associated software is indispensable (Ahmed, Kenkeremath, & Stankovic, 2015). Accordingly, this literature review also aims to identify how and for which purpose knowledge about human emotions can be analysed using mobile devices. Particular attention should be paid to the fact that the measurement is possible ubiquitously and situation-based.

Furthermore, this research should give an overview of the evolution and current types of emotion detection (e.g. biofeedback, facial recognition) as well as of previous research results.

3 Theoretical Background

An emotion is a reaction of the human body to an occurring stimulus like an event of a certain importance. At the same time, emotions lead to high mental activity and can contain high degrees of pleasure or displeasure (Brave & Nass, 2003; Cabanac, 2002). Since emotions manifest in different ways, many researchers try to pinpoint what kind of emotions exist and how they can be categorized (Lövheim, 2012; Plutchik, 2001; Russell, 1980). Emotions are typical human characteristics and have an impact on many aspects of our life, as they influence perception, rational thinking und decision making (Brave & Nass, 2003; Cabanac, 2002; Hussain et al., 2009; Picard, 1995; Reeves & Nass, 1996).

Since humans tend to treat computers like other humans, emotions are also a field of interest in IS research, especially human-computer interactions (Brave & Nass, 2003; Picard, Vyzas, & Healey, 2001). The emotional situation of the user can also be responsible for whether and how he interacts with an IS or other people. An emotion-aware IS therefore may be capable of enhancing the communication and cooperation between human und IS (Hussain et al., 2009). This in turn can lead to a better und more fitting adaptation to the user's situation and to an increased user experience (Peter & Urban, 2012). Thus, it seems reasonable and necessary to enable an IS to perceive, correctly interpret and adequately respond to human emotions (Reeves & Nass, 1996). Since the introduction of the first mass-market smartphone in form of the iPhone by Apple in 2007, the market developed rapidly and an increasing number of people is carrying more and more sensors in their everyday life (Al-Nafjan, Hosny, Al-Ohali, & Al-Wabil, 2017). For the first time it is also possible to derive emotions in a mobile way without the usage of additional equipment. In recent years, further simplifications have been made through the invention of fitness bracelets and smartwatches. Measurement of heart rate, skin conductance as well as voice recording and their transmission to a smartphone are common functional components (Yang, Chang, Chen, Chiang, & Hung, 2014). In a mobile environment, smartphones and smartwatches with their various biometric sensors offer an unobtrusive way of emotion measurement (Bachmann et al., 2015; Likamwa et al., 2013; Muaremi et al., 2013).

The mobile measurement of emotions is captured by Gartner in their well-known Hype Cycle as "Emotion Detection/Recognition". This field of research has been part of the Gartner Hype Cycle for several years. Figure 1 shows the development of this research field in the Gartner Hype Cycle from 2013 to 2018 (e.g. Gartner, 2018b).

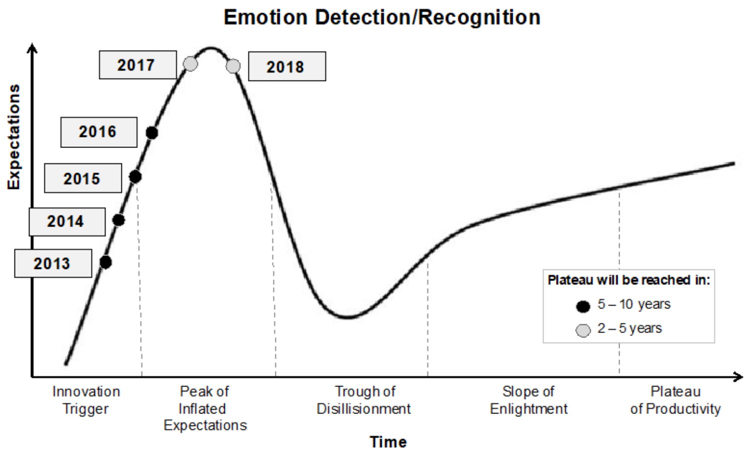

Figure 1: Evolution of "Emotion Detection/Recognition" in the Gartner Hype Cycle from 2013 to 2018

By the year 2018, it has just passed the peak of inflated expectations. According to Gartner, the productivity plateau will be reached in about two to five years. This evolution underlines the growing relevance of the topic, but it also reveals that it is not being used on the mass market yet. (Jannat, Tynes, Lime, Adorno, & Canavan, 2018). Currently, there are hardly any standards for emotion detection, recognition and application, which leads to proprietary developments in the form of in-house prototypes (Vinola & Vimaladevi, 2015). However, emotion measurement is the basis for the future-oriented field of emotional artificial intelligence or emotional AI.

4 Methodical Approach

The methodological approach of this structured literature review and analysis is based on the PRISMA statement by Moher et al. (2010). The research process for this paper is shown in Figure 3.

4.1 Literature Review

First of all, suitable search terms were created to identify the literature were created. The words emotion, measure and mobile form the root of the research question: "How can emotions be measured in a mobile way?". When developing the search query, however, attention was paid to both languages (English and German) and to synonyms of the words. Since the search via the German terms did only lead to one result in the final selection, the analysis using German terms will not be discussed further below. Finally, three categories with four search terms each, were created and Boolean operators were used to link the search terms. Thus, the three categories are linked by the AND operator. Within each category, the synonyms are linked with the OR operator (see Figure 2, left side). It should be noted that in category 2, verbs are mainly used, as they often include the noun (e.g. detect → detection, measure → measurement). Subsequently, the search query was applied to eleven different scientific databases (see Figure 2, right side).

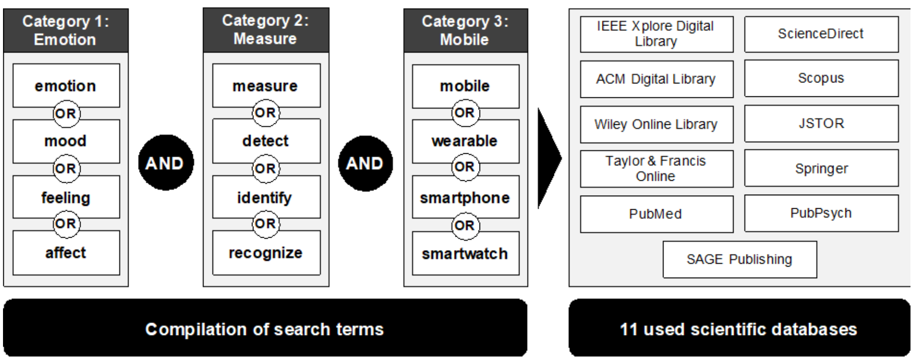

Figure 2: Categorization of search terms and used scientific databases

Since the search is carried out exclusively in the named scientific databases, the results are restricted to literature published in one of these databases. Due to the increasing relevance of the topic since the introduction of the first smartphone (iPhone) in 2007, the restriction begins with publication dates in 2007 and ends in 2018. In addition, the topics were restricted to IS-relevant areas like Internet of Things, Technology, Computer Science, Mobile Computing, Machine Learning. Besides, care has been taken to ensure that the literature was accessible at all time.

At the end of the identification phase, 5,356 entries were found in the scientific databases. However, 565 were deleted during the duplicate cleansing (see Figure 3).

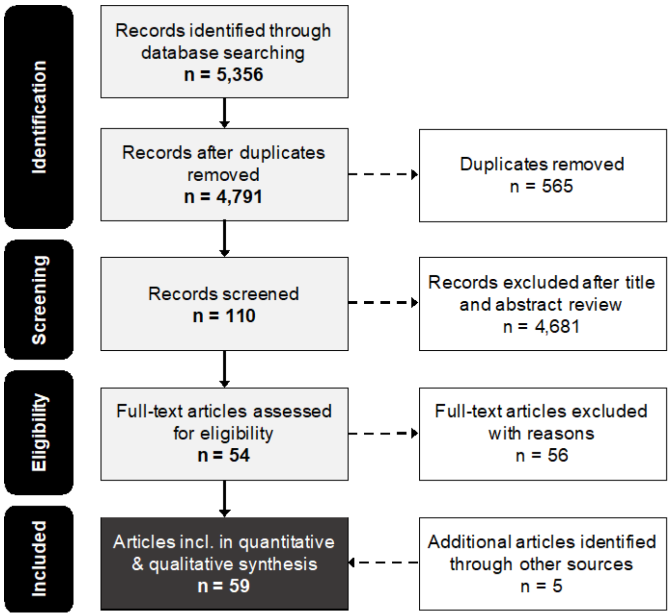

Figure 3: Process of literature selection for mobile measurement of emotions based on the PRISMA statement by Moher et al. (2010)

The literature selection comprises of two further steps. First, all titles and abstracts of the remaining literature were reviewed. Only the literature that dealt directly with the mobile measurement of emotions remained. All literature that did not contain at least two words from different keyword categories and despite previous restrictions fell into subject areas that cannot be used for this research was sorted out. The second step consisted of reading the full-text of the remaining 110 entries. This step also removed all entries that were not accessible as full text.

Finally, using a backward search, additional literature was found by reviewing the literature references of the selected 54 results. Care was taken to ensure that the additional literature also met the criteria mentioned above. Five additional entries were added during the backward search. Finally, 59 entries remained for the full-text analysis.

4.2 Structure of the Literature

The literature used for this paper was roughly structured in order to ensure clarity. For this purpose, the literature was divided into categories according to the various possibilities of emotion recognition. During the evaluation four essential categories were identified (see Figure 4). Optical emotion recognition analyses the user's facial expressions in order to derive his emotions from changes in the mimics. The acoustic emotion recognition concentrates on the voice and speech. In this way, tone, intensity, and tempo of voice are used for evaluation. The vital-data-based emotion recognition uses biofeedback (such as heart rate, skin temperature or skin conductance), which can be measured using different methods. Behavior-based emotion recognition is the recording of emotions using various behavior-related data (such as pedometer, location, light sensor, but also gesture recognition).

1. Optical emotion recognition (Face recognition) Quantity: 12	**2. Acoustic emotion recognition** (Speech recognition) Quantity: 13
3. Vital-data-based emotion recognition (Biofeedback recognition) Quantity: 24	**4. Behavior-based emotion recognition** (Gesture recognition) Quantity: 10

Figure 4: Main categories of identified literature

With the help of these categories it is possible to present and interpret the current state of research. This classification offers a further advantage with regard to the various possible areas of application, since different possible applications arise or disperse depending on the type of measurement. For example, optical recognition can hardly take place when the person being observed is in motion. In contrast, a measurement via biofeedback (vital-data-based) has no difficulties with such a field of application.

5 Evaluation

It is possible to measure emotions by evaluating optical, acoustic, vital-based or behavior-based information of a human. Due to the use of numerous definitions of the term emotion in the remaining literature, it was not possible to make further subdivision.

The definitions range from a simple division into pleasant and unpleasant to the use of complex emotion models like the Circumplex Model of Plutchik (Plutchik, 2001; Weerasinghe et al., 2010). For the purpose of the paper, emotion is defined as follows: An emotion is a pleasant or displeased reaction of the human body triggered by the conscious or unconscious perception of an event or situation (Brave & Nass, 2003; Cabanac, 2002).

5.1 Optical Emotion Recognition

Optical emotion recognition is based on the evaluation of existing image material (Al-Nafjan et al., 2017). For this, the facial expressions of the observed person must be recorded and interpreted. The measurement is often carried out either in a two- or three-dimensional way (Brand, Klompmaker, Schleining, & Weiß, 2012). Current research already tends towards a four-dimensional determination in which time is regarded as the fourth dimension (Kwak & Kim, 2018). These methods analyse facial features, such as eyes, nose and mouth as well as their position, distance and positioning to each other. Subsequently, different algorithms are used to derive emotions from these data.
For a better overview, the literature was further classified according to its research methods (see Table 1). A distinction is made between research in which an application is made available to a user, e.g. through a prototype, and studies which are set up without direct reference to a specific device.

Table 1: Optical Emotion Recognition / Research Method

Research Method	Literature	Number
Study	(Brand et al., 2012) (Kwak & Kim, 2018) (Jannat et al., 2018) (Canavan, Andujar, Yin, Nijholt, & Schotter, 2018) (W. Zhang et al., 2018) (Paleari, Benmokhtar, & Huet, 2009)	6
Application	(Hossain & Muhammad, 2017) (Masai et al., 2017) (Palaniswamy & Tripathi, 2018) (Gu et al., 2018) (Vinola & Vimaladevi, 2015)	6

The high number of studies clearly shows that optical emotion recognition has so far only been possible to a limited extent via mobile devices. Laboratory set-ups are often preferred due to the controllable environment and the computing power that is required. It is repeatedly pointed out that it is also possible to perform these experiments using a smartphone, but a detailed description or implementation is missing (Kwak & Kim, 2018). For a more in-depth analysis, the literature was also classified according to the type of data collection (see Table 2).

Table 2: Optical Emotion Recognition / Data Collection

Data Collection	Literature	Number
Local Binary Patterns	(Paleari et al., 2009) (Hossain & Muhammad, 2017) (L. Zhang, Mistry, Neoh, & Lim, 2016) (Masai et al., 2017)	4
Active shape model	(Palaniswamy & Tripathi, 2018)	1
Convolutional Neural Network	(Jannat et al., 2018) (Kwak & Kim, 2018) (W. Zhang et al., 2018) (Gu et al., 2018)	4
Unclassifiable	(Brand et al., 2012) (Vinola & Vimaladevi, 2015) (Canavan et al., 2018)	3

A large part of the research uses Local Binary Patterns (LBP) as a visual descriptor for image processing. This is already accepted as a standard after its introduction in 1994. Current research from 2018 additionally uses

Convolutional Neural Networks (CNN), which are based on LBP, to achieve better results (Gu et al., 2018). According to Kumar et al. (2017), LBP alone currently has the greatest benefit in relation to effort, with very good results.

Over the years, an increasing improvement in the accuracy and speed of emotion measurement is noticeable. While the accuracy of the research of Paleari et al. (2009) was still below 50 percent in 2009, the accuracy of current research has already risen to over 90 percent (Hossain & Muhammad, 2017; Masai, Itoh, Sugiura, & Sugimoto, 2016). Some measurement is already carried out in real time using smartphones. This supports the trend away from laboratory set-ups, as in 2009 (Paleari et al., 2009), towards the mobile measurement of emotions using smartphones in a mobile environment (Vinola & Vimaladevi, 2015).

5.2 Acoustic Emotion Recognition

Acoustic emotion recognition does not examine speech and words in the true sense, but rather parameters such as tone of the voice, intensity and tempo (Brand et al., 2012). The description of the production of an acoustic signal and the identification of emotions from these signals are not uniform, so that different approaches can be pursued (Park & Jang, 2015).

The selected literature for acoustic emotion recognition is structured by the research method (see Table 3). Many applications use microphones and processors, which could also be integrated into today's smartphones (Yoon, Cho, & Park, 2007).

Most of the studies use very short frames (length approx. 20ms), sometimes up to one minute, to measure emotions (Salekin et al., 2017; Yoon et al., 2007). Due to the high number of frames, high computing power is required. Instead, the applications typically use a longer frame of 5-15 seconds. These frames are further simulated linearly to reduce the computing power and thus make mobile measurement possible using common smartphones. One reason for the high number of existing applications is the increasing number and improving performance of virtual respectively speech assistants (Hossain & Nazin, 2018).

Table 3: Acoustic Emotion Recognition / Research Method

Research Method	Literature	Number
Study	(Vinola & Vimaladevi, 2015) (Yoon et al., 2007) (Salekin et al., 2017) (Ahmed, Chen, Fass, & Stankovic, 2017) (Jannat et al., 2018)	5
Application	(Weerasinghe et al., 2010) (W. Zhang et al., 2018) (Park & Jang, 2015) (Hossain & Nazin, 2018) (Rachuri et al., 2010) (Ahmed et al., 2015) (Gu et al., 2018) (Ma et al., 2018)	8

By classifying the literature according to the type of data collection, it is possible to analyse a temporal progression (see Table 4). While at the beginning of the observation period the characteristics of prosody (accent, intonation, frequency, etc.) were used (2007-2010), the Mel Frequency Cepstrum Coefficients (MFCC) have established themselves as the standard nowadays. In addition, research from 2018 also relies on neural networks (Canavan et al., 2018) or a novel method of micro-prosody, whereby only the frequency of the voice is used for emotion recognition. This should enable a reduction in the amount of data while maintaining the same accuracy (Hossain & Nazin, 2018). Hossain et al. (2018) give detailed descriptions of the functionalities and a comparison of the methods. In comparison, micro-prosody achieves the highest accuracy. In addition to the new features mentioned above, better filtering of background noise offers the possibility to detect emotions over greater distances. The microphone no longer has to be worn directly on the body. This also makes it possible to measure the emotions of several people within a room if they clearly differ in their vocal pitch (Hossain & Nazin, 2018; Salekin et al., 2017). Over time, more and more research is linking optical and acoustic emotion measurement to increase the accuracy of measurement (Vinola & Vimaladevi, 2015; W. Zhang et al., 2018). This measurement is most similar to human perception, in which many different parameters are combined to an overall impression of the emotional state. In addition, more emotions can be distinguished from each other as the distinguishing features become sharper (Brand et al., 2012; Peter & Urban, 2012).

Table 4: Acoustic Emotion Recognition / Data Collection

Data Collection	Literature	Number
Prosody	(Yoon et al., 2007) (Rachuri et al., 2010) (Weerasinghe et al., 2010)	3
MFCC	(Paleari et al., 2009) (Park & Jang, 2015) (Ahmed et al., 2015) (Salekin et al., 2017) (Ahmed et al., 2017) (W. Zhang et al., 2018) (Gu et al., 2018)	7
Micro-prosody	(Hossain & Nazin, 2018)	1
Convolutional neural network	(Ma et al., 2018) (Canavan et al., 2018)	2

5.3 Vital-data-based Emotion Recognition

The category of vital-data-based emotion measurement differs from the two preceding categories essentially as emotion recognition is not possible by simple observation. Here, direct contact between the person and the device or sensor is required (Brand et al., 2012). An advantage at this point is an inconspicuous measurement of the data (e.g. by a smartwatch) which can increase the comfort of the user (Di Lascio, Gashi, & Santini, 2018). Research in this field has been going on for a long time, as it is particularly relevant in the medical field (Geven et al., 2009). Furthermore, there is a direct correlation between biofeedback and a person's emotion (Haag, Goronzy, Schaich, & Williams, 2004). The subdivision of the literature according to the research method shows, as it was already the case with optical or acoustic emotion recognition, that laboratory set-ups are still used frequently (see Table 5). This is particularly due to the increased use in the medical field (Brand et al., 2012). Patients are not treated in their everyday environment, but in rooms that have been prepared for this purpose (Geven et al., 2009).

Table 5: Vital-data-based Emotion Recognition / Research Method

Research Method	Literature	Number
Study	(Leng, Lin, & Zanzi, 2007) (Geven et al., 2009) (Montgomery, 2010) (Perttula, Koivisto, Mäkelä, Suominen, & Multisilta, 2011) (Brand et al., 2012) (Guo et al., 2013) (Vinola & Vimaladevi, 2015) (Exler, Schankin, Klebsattel, & Beigl, 2016) (J. Zhang et al., 2016) (Subramanian et al., 2018) (Mehrotra & Musolesi, 2017) (Al-Nafjan et al., 2017) (Udovičić, Đerek, Russo, & Sikora, 2017) (F. Li et al., 2018)	14
Application	(Gluhak, Presser, Zhu, Esfandiyari, & Kupschick, 2007) (Hussain et al., 2009) (S. Li et al., 2014) (Huynh, Balan, & Lee, 2015) (Carrillo, Meza-Kubo, Morán, Galindo, & García-Canseco, 2015) (Yoon, Sim, & Cho, 2016) (Yasufuku, Terada, & Tsukamoto, 2016) (Zhao, Adib, & Katabi, 2016) (Lam & Szypula, 2018) (Di Lascio et al., 2018)	10

A list of the most frequently used biofeedback (such as skin conductance and heart rate) and their explanation can be found in Haag et al. (2004). A deeper subdivision of the vital-data-based emotion recognition can be made on the basis of the type of biofeedback that is used (see Table 6). In this way, a wide variety of application areas can be distinguished with regard to the sensors or wearables used. When using a smartwatch, the measurement is often limited to heart rate or skin conductance, while specially developed gadgets, such as the glove of the Fraunhofer Institute, record additional vital data like skin temperature (Hussain et al., 2009). Less mobile, but still frequently used, are measurements of brain waves.

Table 6: Vital-data-based Emotion Recognition / Data Collection

Data Collection	Literature	Number
Skin conductance /Skin temperature	(Lam & Szypula, 2018) (Yasufuku et al., 2016) (Huynh et al., 2015) (S. Li et al., 2014) (Guo et al., 2013) (Udovičić et al., 2017)	6
Heart rate	(Exler et al., 2016) (Bachmann et al., 2015) (Zhao et al., 2016) (F. Li et al., 2018)	4
Brain Waves	(J. Zhang et al., 2016) (Al-Nafjan et al., 2017) (Perttula et al., 2011) (Subramanian et al., 2018)	4
Combination	(Yoon et al., 2016) (Vinola & Vimaladevi, 2015) (Leng et al., 2007) (Brand et al., 2012) (Montgomery, 2010) (Geven et al., 2009) (Hussain et al., 2009) (Carrillo et al., 2015) (Gluhak et al., 2007) (Di Lascio et al., 2018)	10

In current research, the increasingly used smartwatches are rarely considered. Only two researches (Bachmann et al., 2015; Exler et al., 2016) use smartwatches for recording. In contrast, there are various in-house developments (Lam & Szypula, 2018; Yasufuku et al., 2016; Yoon et al., 2016) which are connected to a smartphone and are therefore not yet suitable for everyday use. Frequently, these still refer to a medical context and are intended for the preventive identification of dangers to mental and physical health (Yoon et al., 2016). It is assumed that with further technical development of smartwatches a similar performance in emotion recognition will be possible (Huynh et al., 2015; Lam & Szypula, 2018; S. Li et al., 2014). Zhao et al. (2016) show a unique selling point through the contactless measurement of biofeedback. This is done by acoustic resonances from the breathing sounds of humans, which are used to draw conclusions about the heart rate (Zhao et al., 2016).

5.4 Behavior-based Emotion Recognition

Behavioral emotion recognition is a less specific category for the identification of emotions. Here, a combination of several different data sources, which can be picked up by a mobile device, is used to determine emotions (Zhang, Li, Chen, & Lu, 2018). Emotion recognition can be performed by the input behavior of smartphone users (S. Ghosh, Ganguly, Mitra, & De, 2017; Likamwa et al., 2013), the recognition of gestures (Lee, Bae, Lee, & Kim, 2017) as well as by the combination of location, pedometer, smartphone usage and light sensor (Zhang et al., 2018). In the area of behavior-based emotion recognition, no clear trend can be identified with reference to the research method (see Table 7).

Table 7: Behavior-based Emotion Recognition / Research Method

Research Method	Literature	Number
Study	(Tsetserukou & Neviarouskaya, 2010) (Brand et al., 2012) (Yang et al., 2014) (Lee et al., 2017) (Kanjo, Younis, & Ang, 2019)	5
Application	(Coutrix & Mandran, 2012) (Likamwa et al., 2013) (Bachmann et al., 2015) (Surjya Ghosh, Chauhan, Ganguly, Mitra, & De, 2015) (Zhang et al., 2018)	5

Research is still in its infancy and no standard has been established (Kanjo et al., 2019). The studies mainly focus on the analysis of data, while the applications also deal with the integration of analysis methods into everyday life (Zhang et al., 2018).

The further structuring takes place under the mentioned possibilities of emotion recognition, whereby the recognition of gestures and the input behavior are summarized under the point of gesture recognition (see Table 8).

Table 8: Behavior-based Emotion Recognition / Data Collection

Data Collection	Literature	Number
Gesture recognition	(Brand et al., 2012) (Lee et al., 2017) (Likamwa et al., 2013) (Surjya Ghosh et al., 2015) (Coutrix & Mandran, 2012) (Yang et al., 2014) (Tsetserukou & Neviarouskaya, 2010)	7
GPS, light sensors, pedometers, smartphone use, etc.	(Kanjo et al., 2019) (Mehrotra & Musolesi, 2017) (Zhang et al., 2018)	3

The development over time shows a trend towards the use of more and more available data and the bundling of this data to measure emotions (big data analysis). The research by Coutrix & Mandran (2012) and Likamwa et al. (2013) use gesture recognition based on smartphone movement or typing behavior. Recent research tends to use data from as many available sensors as possible. For example X. Zhang et al. (2018) use data from light sensors, GPS, pedometers, smartphone use, as well as audio- and WiFi-usage. The challenge now is to develop a suitable algorithm that can unite the available data in order to identify emotions (Lee et al., 2017).

5.5 Temporal Development of Emotion Measurement

Figure 5 shows the development of the four categories of emotion recognition over time as well as the percentage distribution of all publications. The figure presents the identified literature in the form of four time intervals. There has been a significant increase in the number of scientific articles over the time period considered.

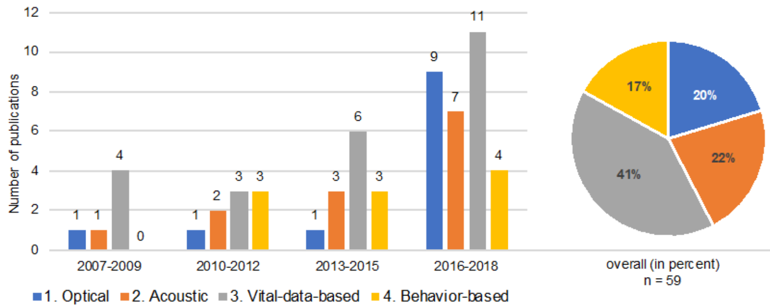

Figure 5: Development of publications over time in the four categories

The lack of literature in the area of behavior-based emotion recognition in the period from 2007 to 2009 shows up as conspicuous. Since very much information is required to analyse behavioral data (Zhang et al., 2018), one possible reason for this lack of literature could lie in the limited technological possibilities in gathering relevant data. With the increasing collection possibilities of data in the last years, this area is growing, but not yet particularly strong.

The development of optical and acoustic emotion recognition, is derived from the areas of speech recognition (e.g. speech assistants) and face recognition (e.g. Face-ID), which are already integrated into a lot of products on the market (W. Zhang et al., 2018). As mentioned before, attempts are being made to combine optical and acoustic emotion recognition (see Chapter 5.2).

Vital-data-based emotion recognition represents the largest share of research over the entire time period (41%). This increase can be explained by the growing implementation of sensors in smartphones and smartwatches (Di Lascio et al., 2018). Due to its suitability for everyday use, this type of emotion recording will presumably be given the highest priority in the future.

6 Conclusions and Outlook

The increasing degree of digitization and the constantly growing technological progress lead to changes in the society and everyday life. Especially smartphones and recently smartwatches offer new possibilities and trend to change the user's behaviour. The user is now able to access the internet anytime and anywhere (Blazquez, 2014). As the demands of every single person on IS are becoming more specific and individual, smart mobile devices offer capabilities for a better and more personalized digital advisory. One way to understand the situation of a human and to offer a situation-aware service is to measure and analyse his emotions.

Consequently, the focus of this systematic literature review was to collect and analyse current possibilities of mobile emotion measurement in IS research. The selection and evaluation of the literature was based on the PRISMA statement by Moher et al. (2010). Eleven databases served as sources for literature analysis to ensure a systematic approach. In this search, the three search term categories emotion, measure and mobile were used.

A total of 59 articles were identified (see Chapter 4), which can be divided into the four main categories of optical, acoustic, vital-data-based and behavior-based emotion recognition and further classified into subgroups (see Chapter 5). The analysis provides a good overview of the areas already researched and suggests future trends. It clearly shows that the relevance of this topic has grown continuously over time. It is noticeable that the speed as well as the accuracy of the emotion measurement has improved considerably. Current studies show an accuracy of at least 90% in all categories and it rises continuously. 10 years ago, the accuracy in some areas was still between 50% and 60%. Accordingly, many researchers are working on mobile emotion measurement in order to facilitate it in our everyday lives. At present, a large number of self-developed sensors are not yet able to be integrated into our mobile daily drivers, like smartphones or smartwatches. This will certainly change in the coming years with an even more digitalised life. The measurement of biofeedback is already most frequently represented at the beginning of the observation period. Due to the increased use of sensors in mobile devices, this method has the greatest potential for the future, since the unobtrusive measurement offers a comparatively large advantage. A major challenge is to transmit the acquired data to useful software, which can deliver a special value to the user. Since emotions can provide good insights into the user's specific situation and thus their needs (Brave & Nass, 2003), there are numerous application areas for the mobile emotion's measurement and usage. With virtual assistants and emotional AI as big future trends, upcoming systems and services should be emphatic (Gartner, 2018a). The big question is whether the society is prepared to reveal this personal data and whether a machine or system should be able to recognize every personal emotion.

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