TECHNICAL REPORT

Survey of contributions for a pipeline of emotion recognition and awareness

Context variables, instruments & sensors, pre-processing techniques and extracted properties for automatic recognition of emotions.

KEYWORDS
Affective Computing; automatic emotion detection; emotional inference; context variables; instruments & sensors; pre-processing techniques; extracted properties.

DATE
2018-12-31

AUTHORS
Célio Carvalho, José Torres and Rui Moreira

ABSTRACT

Emotional assessment has been a research area of health and psychosocial field, since many years. It was from 90's that the recognition of emotions gained more attention from the researchers, becoming an important topic of research up to today (Basu, Bag, Mahadevappa, Mukherjee, & Guha, 2016).

According to Picard, the study of emotions moved from psychology to the area of computing, creating a new research field called Affective Computing (AC). In fact, in her book "Affective Computing", she indicates the basis for creating an intelligent system for automatic emotional detection (R. W. Picard, 1995).

In recent years, there has been an increase in this kind of research, perhaps due the need to transform the interaction between things (e.g. hardware, software and products in general) and people more natural and intelligent (R. Picard & Klein, 2002). This transformed the AC in an important research topic (Bos, 2010).

Several authors believe that the automatic emotional detection can have positive impact on people's lives. As an example, the area of psychology may benefit with less subjectivity, continuous and less deferred data in time; health can be assessed with additional info besides physiological data; it may be easier to detect crimes such as acts of delinquency and terrorist attacks; and it will be easier to design products specialized in provoking or transmitting emotions in the virtual world (Murad & Malkawi, 2012).

It may also be possible to create intelligent affective systems. Emotion-aware systems that can understanding and react to people emotions. Although there are already several studies with the objective of automatically detecting emotions, the authors believe that the correlation of social, cultural, and religious variables with physiological ones, may contribute positively to the quality of the results obtained.

In this context, an experiment is being prepared to automatically detect the well-being of office workers. It is intended to collect context variables of several modalities and, after the pre-processing phase, use that data as input to Machine Learning (ML) classification algorithms. The goal is to verify the possibility of creating intelligent systems from an affective point of view, conscious at the emotional level, capable of perceiving and reacting to the emotions of office workers.

This technical report summarizes the papers studied by the authors during the bibliographic review on the AC topic. A token system is suggested for better categorization of information, and a systematization of information is also proposed through the organization of these tokens in summary tables, to allow an aggregated analysis of the investigations.

The following section summarizes the context variables and domain properties used by the authors. Then, the instruments & sensors used to collect the context variables are presented. Subsequently, the pre-processing techniques used are summarized. It concludes with an enumeration of the extracted properties most used in the studied works.

1. INTRODUCTION

Affective Computing (AC) is a research area focused on detecting people's emotions based on facial, oral, and gestural expressions, and other vital signs of the human body (Gogia, Singh, Mohatta, & Sreejith, 2016) (Zhai & Barreto, 2006) (Zucco, Calabrese, & Cannataro, 2017). The list of application areas includes robotics-based systems, detection of alertness and attention levels (e.g. drivers), game development (e.g. assessment of players' frustration level), eLearning systems for assessment of students' emotional state and attention, etc. (Gogia et al., 2016) (Zhai & Barreto, 2006). In short, AC research develops mechanisms to transform computers into more empathetic instruments (Bos, 2010) and aware of the affective state of their users (Zhai & Barreto, 2006) .

AC systems are generally based on three phases: i) signal acquisition and processing (e.g. expressions (cf. facial, oral or gestural), physiological signals, etc.); ii) mono or multimodal signal combination (i.e. considering signals from only one or several context sources); and iii) emotion classification corresponding to the collected, processed and combined signals (Gogia et al., 2016).

Emotional recognition has been the subject of research in various fields, e.g., automotive, film and game industry, Human-Robot Interaction (HRI), Brain-Computer Interaction (BCI), Human-Computer Interaction (HCI), etc. However, the authors are particularly interested in research related to emotional sensing in intersection with AC research lines.

Driving stress is important for the automotive industry. For e.g. the projects by Paschero (Paschero et al., 2012) and Gutman (Gutmann, Grausberg, Kyamakya, & Klagenfurt, 2015) studied emotions during driving. The former focused directly on stress recognition through images, and the latter studied the various emotions related to the act of driving from physiological variables.

One of the current goals of the film industry is to be able to provoke emotions through stories (Guillotel, Fleureau, Orlac, & Silveira, 2013). The goal of Guillotel's research (Guillotel et al., 2013) was to find ways to continuously collect emotional response during the viewing of a film and not just at the end through questionnaires. In Canini's research (Canini, Benini, Migliorati, & Leonardi, 2009) the authors created an automatic system for emotional rating of movies. The goal of the project was multimedia categorization through an emotional identity that could serve, for example, as a filter in a research process.

There are also several projects in digital games research area. Just as an example, the research of Mandryk and Atkins (Mandryk & Atkins, 2007) aimed to improve user interaction with this type of applications. The authors contributed with a system capable of detecting and continuously representing, in a timeline, the emotional states felt during a game. Another example, and from a different perspective, the authors Hsu, Shih and Chen (Hsu, Shih, & Chen, 2012) wanted to create a game capable of shaping the emotions of the players, teaching them how to transform negative emotions into positive ones.

PROJECT		SUMMARY
Automotive	(Paschero et al., 2012)	Using a video camera, the authors intend to collect images with the aim of detecting stress while driving. The aim of the system is to alert the user when his stress reaches a certain level, to avoid dangerous situations that could endanger his safety and the safety of others.

	(Gutmann et al., 2015)	The authors collect Electroencephalogram (EEG), Electrocardiogram (ECG), Respiratory Inductance Plethysmography (RIP), Heart Rate (HR), Interbeat Interval (IBI), Skin Conductance Response (SCR), acceleration and speed, to detect driving-related emotions (e.g. anxiety, nervousness, or stress) in order to identify potential risk situations, namely those that may negatively influence driver performance.
Film Industry	(Guillotel et al., 2013)	In this project the authors wanted to create an instrument to measure the emotional impact of a film on the user in real time. To this end, they have created a system to detect emotions based on Galvanic Skin Response (GSR) because they believe that this physiological reaction contains non-conscious information about people.
	(Canini et al., 2009)	The framework was created with the goal of being able to characterize multimedia content based on the color, motion and audio of the movie itself. The authors used the Internet Movie Database (IMDb) ("IMDb.com," 2016) and its official rating as irrefutable truth in their study.
Game Industry	(Mandryk & Atkins, 2007)	The authors collected GSR, ECG, HR, and Electromyography (EMG) (from frowning and laughing) to detect emotions. They wanted to find a more objective and continuous way to measure emotions during the game, because the scalar response at the end as with questionnaires, could be influenced by the outcome of the game itself.
	(Hsu et al., 2012)	The goal of the research was to create a 3D game to rationalize the emotional state, teaching how to transform negative emotions into positive ones.
HRI	(Luefeng, Min, Mengtian, Jinhua, & Kaoru, 2016)	The authors have created a system for emotional detection to ease the relationship between humans and robots. The system is based on real-time evaluation of people's facial expressions in order to identify the emotions they feel at each moment.
	(Angel & Bonarini, 2014)	The goal of the research was to find ways for robots to convey emotions without resorting to human expressions and body forms (non-verbal language). The authors chose the change of speed during the movement of the robot as a way to convey emotions to people.
BCI	(Y. Liu, Sourina, & Nguyen, 2010)	The research is based on collecting EEG for the detection of various emotions such as fear, frustration, sadness, joy, etc. The authors chose this input signal because they argue that people cannot tamper with it as can happen in facial expressions and voice intonation.
	(Bos, 2010)	The study also aimed to detect emotions based on the signals produced by the brain. The authors chose this signal because the literature argues that this is the most suitable signal for emotional detection (Choppin, 2000).
	(Chanel, 2009)	The author studies emotional presence in the communication process based on EEG, GSR, respiration, temperature and Bood Volume Pulse (BVP) signals.
HCI	(Chandler & Cornes, 2012)	The authors intended to measure emotional responses in the use of computer programs, as a way to promote better interface design. Facial expression was the base signal collected for detection. However, since it can be manipulated by users, the researchers decided to correlate the signal with the SCR as a way to better ensure the results.
	(Jamshidnejad & Jamshidined, 2009)	The authors present a system for recognizing emotions through facial expressions for use in the online business world. During a transaction, the system created can register the emotions felt by buyers during the purchase.

Similarly, in robotics, ways are being studied for robots to be able to perceive and express emotions, with the goal of smoothing interaction with people (Angel & Bonarini, 2014). In a project by Luefeng (Luefeng et al., 2016) the authors presented robots that could identify and react in real time to people's emotions. The research by Angel and Bonarini (Angel & Bonarini, 2014) studied ways in which robots could express emotions through changes in speed during movement.

There are also several studies that try to detect emotions based on brain activity. In Liu's research (Y. Liu et al., 2010) the authors proposed a real-time emotion detection from the electroencephalogram (EEG) and represented the detected emotions through an avatar. In the papers Bos (Bos, 2010) and Chanel (Chanel, 2009) the authors also collected EEG to detect emotions. In the first case the goal was to make the computer more empathetic with the users, and in the second case the aim was to study emotions as a component of the communication process.

Emotion analysis has also been a very important line of research in the area of HCI (Raudonis, 2013) (Mower, Matari, & Narayanan, 2011). The development of HCI assessment methodologies has diverse origins such as cognitive science, psychology, engineering, and computer science (Norman, 2002). Research in this area already has several works, including some of those already referenced. In this area it is important to know emotionally the reaction of a user when put in contact with a piece of information (Chandler & Cornes, 2012). Knowing whether they were satisfied and enlightened, confused and frustrated, or excited and amused is important for designing interfaces that meet users' expectations (Lisetti & Nasoz, 2004) (Bakhtiyari & Husain, 2014).

The authors Chandler and Cornes (Chandler & Cornes, 2012) argued that the ability of users to successfully interact with applications is crucial. For this reason, they presented a system where the emotions felt while using an application can be recorded for later analysis. Jamshidnejad's project (Jamshidnejad & Jamshidined, 2009) also studied emotional recognition in HCI but from the perspective of online business. The authors argued the importance, for example, of recording users' emotions while browsing and buying products or services on an e-commerce portal.

Although more autonomous, in general systems increasingly interact with humans (Rani, Science, Sarkar, Smith, & Adams, 2003). In this context, AC researchers such as Luefeng (Luefeng et al., 2016) and Rani (Rani et al., 2003), are studying ways to develop systems capable of recognizing and expressing affect with the goal of improving the relationship between human and machine. For this reason, new interdisciplinary lines of research can be expected that look at HCI not only as a way to promote the best possible user experience, but also to satisfy user needs at the emotional level (Bos, 2010).

The studies related to automatic emotion detection follow a generic sequence of steps across different investigations on the subject (Figure 1): i) selection of the context variables to be collected; ii) choice of the instruments and sensors to support the collection; iii) pre-processing of the dataset data (e.g. noise removal, data resizing, etc.); iv) selection of the properties to be extracted; v) choice of the algorithms to be used in emotion classification; and vi) definition of the representative models of the detected emotions.

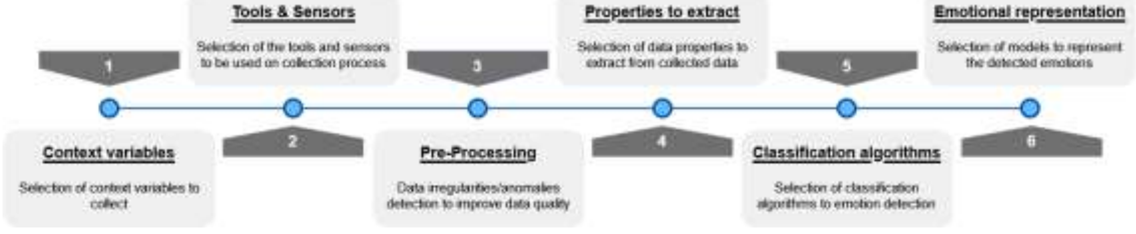

Figure 1 - Generic model used in emotional research

This generic research model can be assumed as a reference to the development process of an emotional detection system, since its specification results from the condensation of the steps followed by projects in the area of automatic emotion recognition, in a standardized way. It is based on this model that the authors believe it is possible to create an intelligent system at the affect level: a system capable of recognizing the emotions of office workers and eventually reacting, reconfiguring the environment with the goal of promoting better well-being in the workplace.

In the following sections, each of the steps of the generic model is discussed in more detail. It is intended to summarize the strategies followed by some of the reference research in the area of automatic emotion detection, surveying the paths already followed and detecting gaps to be considered in the process of creating an emotion-aware system.

In the scope of this bibliographical survey, we decided to analyze the research summarized in the table below. These investigations were chosen because they focus on the automatic detection of emotion, or on other borderline areas.

RESEARCH	SUMMARY	EMOTIONS
Perdiz et al. (Perdiz, Pires, & Nunes, 2017)	Propose a framework that combines the use of the electromyogram (EMG) and the electrooculogram (EOG) to detect emotions.	Anger, sadness, joy, and neutral.
S. H. Lee et al. (S. H. Lee, Member, Ro, & Member, 2016)	Propose a new dynamic recognition method based on facial expressions to solve the problem of temporal mismatches in video sequences (e.g. duration of transitions).	Anger, contempt, disgust, fear, joy, sadness, and surprise.
Eckert et al. (Eckert, Gil, Zapatero, Meneses, & Mart??nez Ortega, 2016)	Present a fast and simple emotion awareness algorithm, capable of running in real-time and in the background, to be reused by other applications (e.g. games).	Anger, grief, fear, sadness, joy, and surprise.
Matlovic et al. (Matlovic, Gaspar, Moro, Simko, & Bielikova, 2016)	Compare emotion detection between electroencephalogram (EEG) (and electrodermal activity (EDA)) sensors and facial expression recognition using existing tools.	Joy, surprise, sadness, fear, grief, anger, and neutral state. *(representation in the two-dimensional valence/arousal model).*
Gogia et al. (Gogia et al., 2016)	Propose a multimodal emotional detection system for use in a learning environment.	Attention state.
Z. Zhang et al. (Z. Zhang et al., 2016)	Present a multi-modal, multi-ethnic, well-annotated emotional database.	Joy, surprise, sadness, fright, embarrassment, fear, pain, anger, and grief.
Sano & Eng (Sano & Eng, 2016)	Study the impact of various factors, such as social interaction, on sleep, stress, mood, and overall well-being.	Stress, mood, and well-being.
Zhao et al. (Zhao, Adib, & Katabi, 2016)	Infer human emotions, using the reflection of wireless signals to replace the traditional electrocardiogram (ECG).	Joy, pleasure, sadness and rage.
Zenonos et al. (Zenonos et al., 2016)	Recognize people's moods by cataloging them into 5 levels of intensity. Researchers see mood as the result of emotions felt.	Excitement, joy, calm, tiredness, boredom, sadness, stress, and anger.
Basu et al. (Basu et al., 2016)	Present a simple emotional recognition system considering nine physiological signals with non-invasive collection.	Valence and arousal.

Aracena et al. (Aracena, Basterrech, Snael, & Velasquez, 2016)	Present an emotional recognition approach based on the information provided by the pupil.	Emotional states: positive, neutral and negative.
Adams & Robinson (Adams & Robinson, 2015)	Present a classifier capable of recognizing complex affective states in a categorical way.	Fear, anger, shame, boredom, disappointment, disgust, excitement, frustration, joy, sorrow, interest, playfulness, pride, sadness, cunningness, surprise, worry, and neutral.
Turan et al. (Turan, Lam, & He, 2015)	Propose an adaptive descriptor-based selection algorithm capable of determining the two best properties of each expression class, with the goals of merging them and thus achieving better recognition.	Anger - grief, fear - surprise, sadness and joy. *(author used the classification into classes following (Jack, Garrod, & Schyns, 2014))*
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	Investigate the emotional content existing in oral speech (read utterances), using Mel Frequency Cepstral Coefficients (MFCC).	Joy, rage, sadness, and neutral.
Lalitha et al. (Lalitha, Mudupu, Nandyala, & Munagala, 2015)	Present a method to identify Discrete Wavelet Transform (DWT) properties suitable for emotion recognition with higher accuracy.	Anxiety, grief, joy, boredom, sadness, anger, and neutral.
Singh et al. (Singh, Sharma, Jain, & Bhall, 2015)	Propose a system that detects a person's emotions and mental state through their body posture.	Disposition (approximate), confusion and doubt, calm and neutral state, laziness or disinterest, and fury.
Murali et al. (Murali, Rincon, & Atienza, 2015)	Introduce a small, lightweight wearable device for physical and emotional health monitoring.	Two-dimensional arousal/valence model.
Jaques et al. (Jaques et al., 2015)	Develop a machine learning algorithm capable of distinguishing between happy and non-joyful students, with the goal of predicting depression.	Happiness.
Cruz et al. (Cruz, Garcia, Pires, & Nunes, 2015)	Present a system for automatic recognition of emotional facial expression based on eye movement.	Human emotions.
Saha et al. (Saha, Datta, Konar, & Janarthanan, 2014)	Create a system to classify emotions based on human body gestures.	Anger, fear, joy, sadness, and relaxation.
Matiko et al. (Matiko, Beeby, & Tudor, 2014)	Present a new fuzzy based algorithm to classify positive and negative emotions from electroencephalogram (EEG).	Valence.
Bogomolov et al. (Bogomolov et al., 2014)	Propose a non-obstructive system for stress recognition based on behavioral metrics.	Stress.
Agrawal et al. (Agrawal, Giripunje, & Bajaj, 2013)	Create a system for detecting fatigue and inattention on the part of the driver, based on face gestures and the emotions deduced from these gestures.	Joy, fury, sadness, and surprise.
Soleymani et al. (Soleymani, Asghari-esfeden, Pantic, & Fu, 2013)	Detect pleasantness (Valence) continuously during the viewing of a video, based on the simultaneous analysis of EEG and facial expression.	Valence. *(axis of the two-dimensional arousal/valence model (excitement or energy / pleasure or pleasantness)).*

Vermun et al. (Vermun, Senapaty, Sankhla, Patnaik, & Routray, 2013)	Create a more accurate system for gesture-based recognition of affective and cognitive state.	Joy, anxiety, disgust, irritation, interest, alertness, boredom, and fatigue. *(positive and negative emotions in a learning environment).*
Kusserow et al. (Kusserow, Amft, & Troster, 2013)	Monitoring stress in speakers, musicians, Olympic athletes, and ordinary people.	Stress.
Alzoubi et al. (Alzoubi, Fossati, D'Mello, & Calvo, 2013)	Study the variation in time of physiological properties that allow the detection of affect.	Affection; Valence and arousal.
Nawasalkar et al. (Nawasalkar, Lawange, Gupta, Butey, & Email, 2013)	Propose a system to recognize the effects of classical and rock music on the human body.	Stress; *(provoked emotions: joy, surprise, sadness and excitement).*
Sano & Picard (Sano & Picard, 2013b)	Find physiological or behavioral signs that function as markers of stress.	Stress.
Raudonis (Raudonis, 2013)	Develop an emotion recognition system based on eye movements.	Neutral, dislike, amusement, and interest.
Kawai et al. (Kawai, Takano, & Nakamura, 2013)	Investigate pupil diameter variation with the goal of being able to measure positive or negative affect in people who cannot move their head or hands to communicate in any other way.	Positive and negative affections.
Babiker et al. (Babiker, Faye, & Malik, 2013)	Identify differences in pupil diameter resulting from individual positive or negative emotional states.	Positive and negative emotions.
LikamWa et al. (LiKamWa, Liu, Lane, & Zhong, 2013)	Develop a smartphone application (MoodScope) capable of inferring the mood of its user.	Disposition.
Murad & Malkawi (Murad & Malkawi, 2012)	Detecting human emotions using a neuro/fuzzy model.	Sadness, joy, fear, embarrassment, heartbreak, anxiety, anger, suspense, relief, pride, and amusement.
C. Y. Chang et al. (Chang, Lin, & Zheng, 2012)	Propose a system based on physiological signals to recognize anger.	Anger.
Bauer & Lukowicz (Bauer & Lukowicz, 2012)	Present a system to detect stress situations using smartphone sensors.	Stress.
Yang & Bhanu (S. Yang & Bhanu, 2011)	Create an avatar (image) representing the emotions of a video or sequence of images.	Anger, fear, joy, relief, and sadness.
Dhall et al. (Dhall, Asthana, Goecke, & Gedeon, 2011)	Propose an automatic emotion recognition method.	Anger, fear, joy, relief, and sadness.
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	Detect stress by analyzing pupil size.	Stress.

Hernandez et al. (Hernandez, Morris, & Picard, 2011)	Measuring stress in a call center environment.	Stress.
N. Lane et al. (N. Lane, Mohammod, Lin, & Yang, 2011)	Propose an application (BeWell) that promotes healthy lifestyle based on the user's daily behavior.	Wellness.
H. Wang et al. (H. Wang, Zhou, & Ying, 2010)	Propose an efficient system to detect fatigue in drivers in real time based on the state of the eye.	Fatigue.
Bos (Bos, 2010)	Create a low-cost, easy-to-install system for emotional recognition.	Representation of recognized emotions in the two-dimensional arousal/valence model.
Y. Liu et al. (Y. Liu et al., 2010)	Create a real-time emotion recognition system. Representation of recognized emotions through an avatar.	Fear, frustration, sadness, joy, pleasantness, and satisfaction. *(emotions determined from the two-dimensional arousal/valence model)*
Setz et al. (Setz et al., 2010)	Distinguish stress from cognitive overwork in an office environment	Stress.
J. Kim & Andre (J. Kim & André, 2008)	Investigate the potential of physiological signals in emotion recognition during music listening.	Valence and arousal.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	Study emotions during film viewing by collecting physiological parameters.	Valence and arousal.
Margaret M. Bradley et al. (Margaret M. Bradley, Miccoli, Escrig, & Lang, 2008)	Assess the hedonic effect of valence and emotional arousal on pupil responses.	Valence and arousal.
Gunes & Piccardi (Gunes & Piccardi, 2007)	Create a system for more accurate affective recognition, based on facial expression and upper body gestures.	Anxiety, rage, grief, fear, joy, and uncertainty.
Castellano et al. (Castellano, Villalba, & Camurri, 2007)	Discover which body movement cues best classify emotions and create a model for emotion recognition based on video analysis.	Anger, joy, pleasure, and sadness.
Mandryk & Atkins (Mandryk & Atkins, 2007)	Detecting and quantifying emotions in the context of affective technologies (e.g. digital games), to avoid measuring only at the end through questionnaires.	Boredom, challenge, excitement, frustration, and fun. *(emotions determined from the two-dimensional arousal/valence model)*
Sebe et al. (Sebe, Cohen, Gevers, & Huang, 2006)	Achieving more accuracy in inferring emotional states by combining the clues given by facial expression and vocal information.	Joy, surprise, anger, disgust, fear, sadness, interest, boredom, confusion, and frustration.
Zhai & Barreto (Zhai & Barreto, 2006)	Present a system for stress detection based on physiological signals collected by non-intrusive sensors.	Stress.

J. A. Healey & Picard (J. A. Healey & Picard, 2005)	Present methods to collect and analyze physiological data during actual driving in order to determine the level of stress.	Stress.
Herbon et al. (Herbon, Peter, Markert, & Meer, 2005)	Finding physiological variables capable of mapping to emotions in an unambiguous way, for use in digital systems.	Valence and arousal.
Partala et al. (Partala, Surakka, & Vanhala, 2005)	Develop an automated system that, in real time, can estimate emotions from the EMG of the face.	Valence.
Van Eck et al. (van Eck, Berkhof, Nicolson, & Sulon, 2005)	To analyze the effects of perceived stress with mood states and stressful daily events, on saliva cortisol levels.	Stress and mood.
Busso et al. (Busso et al., 2004)	Combine facial and oral expression data with the goal of improving accuracy in emotion recognition.	Sadness, anger, joy, and neutral state.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	Develop an HCI system that is sensitive to user emotions, capable of responding to user emotions depending on the context and application.	Sadness, anger, surprise, fear, frustration, and fun.
K. H. Kim et al. (K. H. Kim, Bang, & Kim, 2004)	Develop a user-independent emotion recognition system.	Sadness, anger, stress and surprise.
Haag et al. (Haag, Goronzy, Schaich, & Williams, 2004)	Present a procedure for training computers to recognize emotions from various types of biosensors.	Arousal and valence.
Partala & Surakka (Partala & Surakka, 2003)	Study the variation of pupil size with the application of sound stimuli.	Valence and arousal.
C J Harmer et al. (C J Harmer et al., 2003)	Study the effect of serotonin on emotional disorders.	Joy, sadness, fear, anger, and grief.
Nwe et al. (Nwe et al., 2001)	Propose a system to automatically classify emotions based on spoken speech.	Anger, dislike, fear, joy, sadness, and surprise.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	Study the impact of cortisol on human memory, using images to stimulate emotional arousal.	Arousal.
Jennifer a Healey (Jennifer a Healey, Picard, & Smith, 2000)	Study of stress while driving.	Stress while driving. (preliminary experience) Anger, hatred, sadness, love, joy, reverence, and neutral state.
Vrijkotte et al. (Vrijkotte, van Doornen, & de Geus, 2000)	Study of stress at work.	Stress.
Ritz et al. (Ritz, Steptoe, DeWilde, & Costa, 2000)	To study the impact of different emotional states and stress on oscillatory resistance (ROS) in asthmatics and non-asthmatics.	Anxiety, anger, depression, joy, happiness, contentment, and neutral; Stress.

L. S. Chen et al. (L. S. Chen, Huang, Miyasato, & Nakatsu, 1998)	Integrate audio and video to promote better emotion recognition.	Joy, sadness, anger, dislike, surprise and fear.
J. Healey & Picard (J. Healey & Picard, 1998)	Present a method for pattern recognition in context data, representing affective states of the user.	Anger, hatred, affliction, familial love, romantic love, joy, reverence (deep respect). Arousal and valence.
Rajita Sinha (Rajita Sinha, 1996)	Detecting emotions in humans, using EMG in the muscles of the face and the EOG to monitor vertical and horizontal eye movement.	Fear, joy, sadness, and anger.
Scott R. Vrana (Scott R. Vrana, 1993)	Study the differences between physiologically classified and reported emotions, differentiate negative emotions, and study the muscular reactions of the face.	Disgust, fury, pleasure, and joy.
R Sinha et al. (R Sinha, Lovallo, & Parsons, 1992)	Study the patterns of cardiovascular activity during different emotional states.	Joy, sadness, fear, and anger.

2. CONTEXT VARIABLES AND DOMAIN PROPERTIES

Emotions cannot be measured directly. For that reason, researchers collect contextual data from people to discover them (Kreibig, 2010). These input signals can be of multimodal origin: facial, oral, or bodily expression; physiological signals from the human body; (Jerritta, Murugappan, Nagarajan, & Wan, 2011) (Sim, Jang, & Park, 2007) (Chang et al., 2012); and subjective feelings (Scherer & Ekman, 1984).

In this section the context variables collected by the authors of the analyzed papers are presented. In addition to the raw data obtained directly from the collection instruments and sensors, domain properties (i.e. properties extracted directly from the input signal, whose method of obtaining is confusable with that used in the acquisition of the original signal itself) are also considered in this section (e.g. Heart Rate (HR) is a measure determined automatically by the collection instrument (e.g. electrocardiogram (ECG), photoplethysmography (PPG), etc.)). Since many of these measures are automatically calculated by the collection instruments themselves, and other researchers also consider them as context variables, we also decided to include these properties in the context variables section rather than in the extracted properties section (i.e. section 5).

It was decided to use the notation *OriginalSignal(DomainProperty)* to represent the signal chain and its domain properties (e.g. ECG(HR) and PPG(HR)).

The following table summarizes the various context variables (and domain properties), used by the authors of the research analyzed.

DESCRIPTION	ID	ORIGIN	GROUP *(mode or category)*
FACIAL EXPRESSION, ORAL EXPRESSION AND BODY POSTURE			
Arms	**ARMS**	Data collected from image or video.	Body Posture
Combined action units	**CAU**	Agglomeration of several AUs from the FACS system.	Facial Expression
Cheeks	**CHEEKS**	Data collected from image or video.	Facial Expression
Chin (chin)	**CHIN**	Data collected from image or video.	Facial Expression
Elbows	**ELBOWS**	Data collected from image or video.	Gesture Expression
Eyebrows	**EYEBROWS**	Data collected from image or video.	Facial Expression
Eyelids	**EYELIDS**	Data collected from image or video.	Facial Expression
Eyes	**EYES**	Data collected from image or video.	Facial Expression
Facial action coding system	**FACS**	Data collected from image or video.	Facial Expression
Fingers	**FINGERS**	Data collected from image or video.	Gesture Expression
Fists	**FISTS**	Data collected from image or video.	Gesture Expression
Forehead	**FOREHEAD**	Data collected from image or video.	Facial Expression
Frown	**FROWN**	Data collected from image or video.	Facial Expression
Hands**...**	**HANDS**	Data collected from image or video.	Gesture Expression
Head	**HEAD**	Data collected from image or video.	Facial and gestural expression
Hip	**HIP**	Data collected from image or video.	Body Posture
Jaw	**JAW**	Data collected from image or video.	Facial Expression
Knees	**KNEES**	Data collected from image or video.	Body Posture

Lips	**LIPS**	Data collected from image or video.	Facial Expression
Mouth	**MOUTH**	Data collected from image or video.	Facial Expression
Neck	**NECK**	Data collected from image or video.	Gesture Expression
Nose	**NOSE**	Data collected from image or video.	Facial Expression
Palm	**PALMS**	Data collected from image or video.	Gesture Expression
Pitch (perception of sound quality)	**PITCH**	Data collected from audio or video.	Oral Expression
Shoulders	**SHOULDERS**	Data collected from image or video.	Gesture Expression
Skin	**SKIN**	Data collected from image or video.	Facial Expression
Speech	**SPEECH**	Data collected from audio or video.	Oral Expression
Spine	**SPIN**	Data collected from image or video.	Gesture Expression
Tone (manner of speaking)	**TONE**	Data collected from audio or video.	Oral Expression
Volume (energy, intensity or volume)	**VOLUME**	Data collected from audio or video.	Oral Expression
Wrinkles	**WRINKLES**	Data collected from image or video.	Facial Expression
Wrists	**WRISTS**	Data collected from image or video.	Gesture Expression
PHYSIOLOGICAL CONTEXT VARIABLES			
Blood pressure	**BP**	Sphygmomanometers, stethoscopes, phonocardiograms and electronic palpation (Sorvoja & Myllylä, 2006)). It can be obtained from the PTT (Špulák, Čmejla, & Fabián, n.d.) (R. Wang, Wenyan Jia, Zhi-Hong Mao, Sclabassi, & Mingui Sun, 2014) SBP and DBP, and PPG (Chanel, 2009) (Kusserow et al., 2013) and the correlation of data between EEG and PPG (Špulák et al., n.d.).	Cardiac activity
Blood volume pulse	**BVP**	PPG (Chanel, 2009) (Jennifer a Healey et al., 2000) (Peper, Harvey, Lin, Tylova, & Moss, 2007) (e.g. (Plux, 2017)).	Cardiac activity
Cardiac **output**	**CO**	It can be estimated from BP (Biopac Systems, 2017) or from ICG data (R Sinha et al., 1992). Geerts et al. presents several methods for measuring CO (Geerts, Aarts, & Jansen, 2011).	Cardiac activity
Cortisol (cortisol)	**CORT**	Levels can be measured in blood, urine, or saliva (Frazão, 2016a). It can also be measured through hair (Gow, Thomson, Rieder, Van Uum, & Koren, 2010).	Glandular activity
Diastolic **blood pressure**	**DBP**	Measured based on BP (Sorvoja & Myllylä, 2006). It can be estimated from the PTT (R. Wang et al., 2014), or from the ECG and PPG (Špulák et al., n.d.).	Cardiac activity
Electrocardiogram	**ECG**	Sensor.	Cardiac activity
Electrodermal **activity**	**EDA**	Collection done via sensors placed on the skin, e.g., in the palm of the hand (Z. Zhang et al., 2016) or on the fingers (J. Kim & André, 2008).	Skin
Electroencephalogram	**EEG**	Sensor.	Brain activity
Electromyogram	**EMG**	Measured using sensors that collect the electrical voltages of muscle contraction (Jennifer a Healey et al., 2000) (J. Kim & André, 2008) (Lichtenstein, Antje; Oehme, 2008)	Muscle activity
Electrooculogram (electrooculogram)	**EOG**	Collection using electrodes placed on the eye area to detect motion based on the voltage difference between the cornea and the retina (J. Zhang, Guo, Hong, & Zhang, 2013).	Eye activity
Heart **rate**	**HR**	Can be extracted from the ECG (Jennifer a Healey et al., 2000) (Kusserow et al., 2013) (Jennings et al.,	Cardiac activity

		1981) (Mandryk & Atkins, 2007) ICG or PPG (Kusserow et al., 2013). It can be deduced from the IBI (Chanel, 2009), the BP or the BVP (Jennings et al., 1981) (Peper et al., 2007).	
Heart rate variability	**HRV**	It can be taken from the ECG (Kusserow et al., 2013) (Jennifer a Healey et al., 2000) (Mandryk & Atkins, 2007) (Stephens, Christie, & Friedman, 2010). It can also be deduced from the HR or the IBI (Chanel, 2009).	Cardiac activity
Inter-beat interval	**IBI**	Calculated from ECG (Stephens et al., 2010) (Chanel, 2009) (Mandryk & Atkins, 2007) (Kreibig, 2010).	Cardiac activity
Impedance cardiogram	**ICG**	Sensor.	Cardiac activity
Left ventricular **ejection time**	**LVET**	Calculated from the ICG (Stephens et al., 2010).	Cardiac activity
Mean **arterial pressure**	**MAP**	Average of several PRs collected over a period of time (Chanel, 2009) (Solà i Carós, 2011).	Cardiac activity
Melatonin	**MELAT**	Levels can be measured in blood or saliva (Frazão, 2016b).	Glandular activity
Non-invasive blood **pressure**	**NIBP**	Calculated from PTT, or directly from ICG or ECG (Murali et al., 2015).	Cardiac activity
Nonspecific **skin conductance** response	**nSRR**	Sensor (see EDA).	Skin
Phonocardiogram	**PCG**	Sensor (heart sounds).	Cardiac activity
Pre-ejection **period**	**WBS**	It can be extracted from the conjugation of ECG and ICG (Murali et al., 2015) (Backs, Navidzadeh, & Xu, 2000).	Cardiac activity
Phtoplethysmography	**PPG**	Sensor.	Cardiac activity
Pulse **rate**	**PR**	Sensor (e.g. (Harsono, 2012);	Cardiac activity
Pulse **Transit Time**	**PTT**	It can be calculated based on the delay between ECG and ICG (Murali et al., 2015) (R. Wang et al., 2014) or from the ECG and PPG measured on the finger (Hey et al., 2009).	Cardiac activity
Pupil	**PUPIL**	The sensor that collects pupil movement and dilation (e.g. infrared camera in conjunction with an infrared light source (SR Research, 2017)) (Aracena et al., 2016) (Raudonis, 2013).	Eye activity
Peripheral vascular **resistance**	**PVR**	Calculated, for example, based on ICG data (R Sinha et al., 1992) but there are several methods for its determination (Müller & Martin, 1992).	Cardiac activity
Breath depth	**RDEP**	Determined based on the amount of elastic elongation of the belt that measures the expansion of the chest cavity (J. Kim & André, 2008).	Respiratory activity
Respiration	**RESP**	Respiratory activity measured using sensors that quantify the gas expelled from the lungs, or chest cavity expansion (belt) sensors (Jennifer a Healey et al., 2000) (Z. Zhang et al., 2016).	Respiratory activity
Root-meam-square **of successive differences**	**RMSSD**	It allows, for example, to determine the HRV (Biopac Systems Inc, 2017b) (DeGiorgio et al., 2010) (Kreibig, 2010).	Cardiac activity
Oscillatory resistance	**ROS**	A sensor that measures the resistance occurring in breathing by also considering tissue resistance. It can also be calculated from a cheek plethysmography (volume variation) (Ritz et al., 2000).	Respiratory activity
Respiration **rate**	**RR**	Sensor (see RESP); It can also be deduced from the ICG by removing the high frequency oscillations from the HR, the low frequencies correspond to the breathing frequency (Murali et al., 2015).	Respiratory activity

Systolic **blood pressure**	**SBP**	It can be collected by the BP methods (Sorvoja & Myllylä, 2006), estimated from the PTT (R. Wang et al., 2014), or from the ECG and PPG (Špulák et al., n.d.).	Cardiac activity
Standard **Deviation of NN Intervals**	**SDNN**	It can be calculated from the IBI is a measure used in emotional recognition systems (e.g. Zhao et al. (Zhao et al., 2016)).	Cardiac activity
Serotonin (serotonin)	**SEROT**	Levels can be measured in blood or urine (Visser et al., 2011) (Source, 2015) (Nichkova et al., 2012).	Glandular activity
Skin temperature	**ST**	Sensor (e.g. thermometer, thermal camera (Z. Zhang et al., 2016)).	Skin
Stroke volume (systolic volume)	**SV**	Can be extracted from the ICG (Willemsen, De Geus, Klaver, Van Doornen, & Carroll, 1996) (Kusserow et al., 2013) although there are still some reservations about this method (Stephens et al., 2010).	Cardiac activity
Vagal **tone**	**VAGAL**	It refers to the activity of the vagus nerve, an important component of the parasympathetic system of the autonomic nervous system (Porges, 1995).	Cardiac activity
Tidal volume	**VT**	Calculated based on the amount of gas dispensed in a normal (effortless) inspiration and expiration (Murad & Malkawi, 2012).	Respiratory activity
PSYCHOSOCIAL CONTEXT VARIABLES			
Academic Curricular **Activity**	**ACADCL**	Questionnaire.	Recognition (other domains)
Academic degree	**ACADDG**	Questionnaire.	Recognition (other domains)
Academic Extracurricular **Activity**	**ACADEX**	Questionnaire.	Integration (other domains)
Academic **grades**	**ACADGR**	Questionnaire.	Recognition (other domains)
Academic Study **Time**	**ACADST**	Questionnaire.	Recognition (other domains)
Age	**AGE**	Questionnaire.	Demographic (personal domain)
Alcohol intake	**ALCOH**	Questionnaire.	Integration (other domains)
Alert felt, level of... (alert level)	**ALERT**	Questionnaire.	Psychosocial (personal domain)
Anger felt, level of... (level of anger felt)	**ANGER**	Questionnaire.	Psychosocial (personal domain)
Anxiety felt, level of... (level of anxiety felt)	**ANXIETY**	Questionnaire.	Psychosocial (personal domain)
Apps usage	**APPS**	Usage history of the computer, smartphone, smartwatch or tablet.	Daily routine (personal domain)
Body Mass Index	**BMI**	Questionnaire or calculation.	Recognition (other domains)
Browser usage	**BROWSER**	Usage history of the computer, smartphone, smartwatch or tablet.	Daily routine (personal domain)
Caffeine intake	**CAFFEI**	Questionnaire.	Integration (other domains)

Phonecalls (phone calls)	**CALL**	Call history from the smartphone (e.g. MoodScope (LiKamWa et al., 2013) funf (Aharony & Gardner, 2011), etc.).	Interaction (other domains)
Calm felt, level of**...**	**CALM**	Questionnaire.	Psychosocial (personal domain)
Depression felt, level of... (level of depression felt)	**DEPRESSION**	Questionnaire.	Psychosocial (personal domain)
Difficulties**, life...**	**DIFFICULTIES**	Questionnaire or interview.	Psychosocial (personal domain)
Drugs intake (alcohol intake)	**DRUGS**	Questionnaire.	Integration (other domains)
Electronic devices usage	**ELECTR**	Questionnaire or sensors of electrical consumption.	Daily routine (personal domain)
Email (electronic mail)	**EMAIL**	Email history from computer or smartphone (e.g. MoodScope (LiKamWa et al., 2013) funf (Aharony & Gardner, 2011), etc.).	Interaction (other domains)
Emotions felt	**EMOTIONS**	Questionnaire.	Psychosocial (personal domain)
Energy felt, level of... (level of energy felt)	**ENERGY**	Questionnaire.	Psychosocial (personal domain)
Ethnicity	**ETHNICITY**	Questionnaire.	Demographic (personal domain)
Food, information about... (information about food)	**FOOD**	Questionnaire.	Integration (other domains)
Gender	**GENDER**	Questionnaire.	Demographic (personal domain)
Happiness felt, level of... (level of happiness felt)	**HAPPY**	Questionnaire.	Psychosocial (personal domain)
Health **status felt**	**HEALTH**	Questionnaire.	Psychosocial (personal domain)
Height	**HEIGHT**	Questionnaire.	Recognition (other domains)
Job (profession)	**JOB**	Questionnaire.	Recognition (other domains)
Life events, recent landmark... (recent landmark events)	**LIFEEVENTS**	Questionnaire or interview.	Psychosocial (personal domain)
Living situation	**LIVING**	Questionnaire.	Demographic (personal domain)
Localization, geo... (geolocation)	**LOCATION**	Global Position System (GPS) or Wireless Fidelity (WiFi) collected from the smartphone or other GPS or WiFi enabled equipment.	Daily routine (personal domain)
Mail, traditional... (traditional mail)	**MAIL**	Questionnaire.	Interaction (other domains)
Mood status felt	**MOOD**	Questionnaire.	Psychosocial (personal domain)

Nap data	**NAP**	Questionnaire.	Psychosocial (personal domain)
Personality data	**PERSON**	Questionnaire (e.g. Big Five Inventory Personality Traits (McCrae & John, 1992))	Psychosocial (personal domain)
Physical activity	**PHYSI**	Questionnaire.	Recognition (other domains)
Proximity interaction	**PROXIMITY**	History of new equipment recognition (e.g. bluetooth discovering).	Interaction (other domains)
Race	**RACE**	Questionnaire.	Demographic (personal domain)
Study area in the school	**SCHOOLA**	Questionnaire.	Demographic (personal domain)
School year (actual)	**SCHOOLY**	Questionnaire.	Demographic (personal domain)
Screen on and off, **toggle...**	**SCREEN**	Usage history of the smartphone, smartwatch or tablet.	Daily routine (personal domain)
Sleep data	**SLEEP**	Questionnaire.	Psychosocial (personal domain)
Smoking, information about...	**SMOKING**	Questionnaire.	Integration (other domains)
SMS **messages**	**SMS**	SMS history from the smartphone (e.g. MoodScope (LiKamWa et al., 2013); funf (Aharony & Gardner, 2011); etc.)	Interaction (other domains)
Social interactions, quality of**...**	**SOCIAL**	Questionnaire.	Interaction (other domains)
Stress felt, level of... (level of stress)	**STRESS**	Questionnaire.	Psychosocial (personal domain)
Talk, time of... (time of conversation)	**TALK**	Microphone usage history (e.g. from smartphone)	Interaction (other domains)
Technological experience	**TECHEXPERT**	Questionnaire or interview.	Daily routine (personal domain)
Tired felt, level of**...**	**TIRED**	Questionnaire.	Psychosocial (personal domain)
Waist **size**	**WAIST**	Questionnaire.	Recognition (other domains)
Weight	**WEIGHT**	Questionnaire.	Recognition (other domains)
Wellbeing felt, level of**...**	**WELLBEING**	Questionnaire.	Psychosocial (personal domain)
Work, years of**...**	**WORKYEARS**	Questionnaire.	Recognition (other domains)
OTHER VARIABLES			
Temperature	**TEMP**	Thermometer.	Other variables
Light, ambient...	**LIGHT**	Brightness sensors.	Other variables
Acclerometer	**ACC**	(e.g. Toshiba Silmee™ W20/W21 (Toshiba, 2015))	Other variables
Weather **conditions**	**WEATHER**	Determined based on sensor data: temperature; ambient; humidity; visibility; wind; number of hours of sunshine and rain; etc.	Other variables

2.1. FACIAL EXPRESSION, ORAL EXPRESSION AND BODY POSTURE

The voice is the human being's primary form of communication (Nwe et al., 2001) and its content is decorated with body expression and intonation, with the aim of enriching the transmitted message with emotional ornaments (Ekman, Paul; Freiesen, 2003) (Lisetti & Nasoz, 2004) (Birdwhistell, 1970).

Communication between people consists of both verbal and nonverbal aspects, and it is essentially through nonverbal communication that humans communicate emotions (Singh et al., 2015) (Nawasalkar et al., 2013). The ability to express them can be considered as essential in the processes of communication and understanding between people (Lopes, Salovey, & Straus, 2003) (Raudonis, 2013).

There are several researchers who choose the properties of verbal and nonverbal communication as input signals in their emotional recognition systems. The reason will be the ease of data collection in these modalities when compared to others whose collection process will be more intrusive (e.g. physiological signals).

2.1.1. Facial Expression

Facial expression varies with some emotions and is one of the most used ways for humans to express how they feel (Recognition, 2009) (Chandler & Cornes, 2012). This form of expression and head movement are important sources of information for communicating people's mental state (Adams & Robinson, 2015). Although the detection of emotions based on this type of expression has a long history (Haag et al., 2004) new studies continue to emerge in an attempt to improve recognition accuracy based on facial expression (Eckert et al., 2016) (Matlovic et al., 2016).

There are two types of approaches to emotional recognition through facial expression. Those based on appearance in which the authors use specific descriptors, which will be discussed in section 5 - extracted properties, and those based on the geometry of the face components that will be presented next.

Approaches based on geometric properties use information about the dynamics of face elements that change depending on people's emotional state and movement (Turan et al., 2015). Of the various components of the face **(FACE)** considered by researchers, the following will be most used: head (**HEAD)**; forehead **(FOREHEAD)**; eyes **(EYES)**; eyebrows **(EYEBROWS)**; eyelids **(EYELIDS)**; cheeks (**CHEEKS)**; nose (**NOSE)**; mouth **(MOUTH);** lips (**LIPS);** chin (**CHIN);** jaw (**JAW)**; and skin **(SKIN)**. Some authors also analyze the existence of wrinkles (e.g. formed by the mouth, nose, and forehead area): wrinkle **(WRINKLES)**; and frown **(FROWN)**.

The Facial Action Coding System **(FACS)** is a standard that defines the contours for emotion recognition through facial expression (Fasel & Luettin, 2003). The division of the face into zones makes it possible to detect localized internal motion from muscle monitoring (Ekman, Paul; Friesen, 1978). The researchers Eckert et al. (Eckert et al., 2016) presented the concept of Combined Action Units **(CAU)** that group Action Units (AU) from the FACS system. For example, muscle movement in the AU7, AU23, and AU24 group will signify anger, and activity in the AU9 and AU10 group could signify disgust (Eckert et al., 2016).

RESEARCH	CONTEXT VARIABLES	
	FACIAL EXPRESSION	OTHER
Perdiz et al. (Perdiz et al., 2017)	HEAD.	**(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG.
S. H. Lee et al. (S. H. Lee et al., 2016)	FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH).	
Eckert et al. (Eckert et al., 2016)	FACS, CAU, EYES, EYEBROWS, NOSE, and MOUTH.	
Matlovic et al. (Matlovic et al., 2016)	Authors used FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017) to recognize emotions from facial expressions. EYES *(unprocessed signal).*	**(A. CEREBRAL)** EEG. **(SKIN)** EDA. **(PSYCHOSOCIAL)** EMOTIONS.
Gogia et al. (Gogia et al., 2016)	HEAD.	**(A. CEREBRAL)** EEG.
Z. Zhang et al. (Z. Zhang et al., 2016)	HEAD and FACS.	**(A. CARDÍACA)** BP(SBP, DBP), HR and PR. **(A. RESPIRATORY)** RESP(RR). **(SKIN)** EDA and ST. **(PSYCHOSOCIAL)** EMOTIONS.
Adams & Robinson (Adams & Robinson, 2015)	FACS (HEAD, EYES, EYEBROWS, EYELIDS, CHEEKS, WRINKLES, NOSE, LIPS, CHIN, JAW).	**(A. OCULAR)** GAZE.
Turan et al. (Turan et al., 2015)	FACE and EYES.	
Agrawal et al. (Agrawal et al., 2013)	EYES, MOUTH, LIPS, and SKIN.	
Soleymani et al. (Soleymani et al., 2013)	HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH.	**(A. CEREBRAL)** EEG. **(PSYCHOSOCIAL)** EMOTIONS.
Vermun et al. (Vermun et al., 2013)	HEAD, LIPS, MOUTH, and EYEBROWS. *The authors treat these variables as gestural expression.*	**<u>Gesture expression and posture:</u>** SHOC, HIP, KNEL and KNER.
Yang & Bhanu (S. Yang & Bhanu, 2011)	HEAD and FACE.	
Dhall et al. (Dhall et al., 2011)	FACE.	
H. Wang et al. (H. Wang et al., 2010)	EYES.	
Gunes & Piccardi (Gunes & Piccardi, 2007)	LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD and JAW.	**<u>Gesture expression and posture:</u>** SHOULDERS, HANDS, FINGERS, FISTS, PALMS, and NECK.
Sebe et al. (Sebe et al., 2006)	HEAD, EYEBROWS, EYELIDS, and MOUTH.	**<u>Oral expression:</u>** VOLUME, SPEECH and PITCH.
Busso et al. (Busso et al., 2004)	FOREHEAD, EYEBROWS, EYES and CHEEKS.	**<u>Oral expression:</u>** PITCH and VOLUME.

L. S. Chen et al. (L. S. Chen et al., 1998)	EYES, EYEBROWS, MOUTH, WRINKLES, and FROWN.	**Oral expression:** SPEECH and PITCH.

() represents a raw signal

2.1.2. Oral Expression

In recent years there have been several investigations that have combined facial expression with the spoken expression signal, with the aim of improving accuracy in emotional recognition (Jerritta et al., 2011).

The main challenge posed to emotion recognition systems from **spoken expression** will be the choice of data to collect from the context. The properties should be independent of the speaker and mirror the emotional part of the oral content (Shegokar & Sircar, 2016)..

From intonation **(SPEECH)** it is possible to extract several properties related to nonverbal communication (Rani & Sarkar, 2006). The emotions felt at the moment of speaking tend to influence the pitch, speed, quality and articulation of words (Cahn, 1990)(Cahn, 1990) , making this set of acoustic features a good candidate for the input signal of a system for affective recognition (Rani & Sarkar, 2006) (Haritaoglu et al., 2001). Part of this set are the properties: pitch (perceived sound quality) **(PITCH)**; energy, intensity or volume **(VOLUME)**; and tone (**TONE)**.

RESEARCH	CONTEXT VARIABLES	
	ORAL EXPRESSION	OTHER
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	SPEECH and VOLUME.	
Lalitha et al. (Lalitha et al., 2015)	SPEECH, PITCH and VOLUME.	
Sebe et al. (Sebe et al., 2006)	VOLUME, SPEECH, and PITCH.	**Facial expression:** HEAD, EYEBROWS, EYELIDS, and MOUTH.
Busso et al. (Busso et al., 2004)	PITCH and VOLUME.	**Facial expression:** FOREHEAD, EYEBROWS, EYES and CHEEKS.
Nwe et al. (Nwe et al., 2001)	SPEECH.	
L. S. Chen et al. (L. S. Chen et al., 1998)	SPEECH and PITCH.	**Facial expression:** EYES, EYEBROWS, MOUTH, WRINKLES, and FROWN.

() represents a raw signal

2.1.3. Gesture expression and posture

Gestural expression is important in people's communication and interaction, but it is very dependent on the cultural and social context (Rehm, Bee, & André, 2008). It is an important indicator of a person's mental state, and consequently an important indicator of the mental state of a person. Still, it is an important indicator of people's mental state and, consequently, an important data source for an emotional inference system (Saha et al., 2014).

Gestures are expressive body movements and involve the vast majority of the time, only the face and hands (Saha et al., 2014). Using only upper limb information as they believed it to be sufficient for emotional recognition, researchers Saha et al. used the **Kinect** (Leyvand, Meekhof, Wei, Sun, & Guo, 2011) to collect the following context data: head **(HEAD)**, spine **(SPIN)**, hands (**HANDS),** wrists (**WRISTS)**, elbows **(ELBOWS),** and shoulders **(SHOULDERS)**. The study aimed to identify gestures and map them with emotional states. The input of the system was based on geometric measurements determined on the basis of joint coordinates (cf. distances, acceleration, and angles) (Saha et al., 2014).

Gunes and Piccardi also created a system for emotion recognition based on the upper body limbs, but focused primarily on signals produced by finger movement **(FINGERS)**, fist or closed hand (**FISTS),** palms **(PALMS),** and hand movement near the neck **(NECK**) (Gunes & Piccardi, 2007).

Body posture is also used by some researchers for emotional assessment. Vermen et al. combined data collected from gesture expression with body posture to identify prominent affective and cognitive states in the classroom (Vermun et al., 2013). In addition to other data, the researchers considered information about hip **(HIP)** and knee **(KNEES)** movement.

The literature indicates that different emotions are associated with different types of body movement. In this context, researchers Catellano et al. collected data related to arm movement **(ARMS)** to analyze emotions from the gesture of raising them in the coronal plane (Castellano et al., 2007).

RESEARCH	CONTEXT VARIABLES	
	EXP. GESTURE AND POSTURE	OTHER
Singh et al. (Singh et al., 2015)	SHOULDERS and HANDS.	
Saha et al. (Saha et al., 2014)	HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, and SPIN.	**(OTHER)** ACC.
Vermun et al. (Vermun et al., 2013)	ARMS, SHOULDERS, HIP, and KNEES.	**Facial expression*:** HEAD, LIPS, MOUTH, and EYEBROWS. **the authors treat these variables as gestural expression.*
Gunes & Piccardi (Gunes & Piccardi, 2007)	SHOULDERS, HANDS, FINGERS, FISTS, PALMS, and NECK.	**Facial expression:** LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD and JAW.
Castellano et al. (Castellano et al., 2007)	ARMS.	

() represents a raw signal

2.1.4. Analysis

There are several challenges facing research that relies on body expression as input to emotional recognition systems.

Humans can control facial expressions and intonation (Y. Liu et al., 2010). People tend to hide their feelings as a way to avoid exposure to the group. Since they can suppress or tamper with the emotional content of their expressions or their voice (K. H. Kim et al., 2004) this source of context data may lead to erroneous recognition of emotions by the systems (Jerritta et al., 2011) (Chang et al., 2012).

Furthermore, systems that recognize emotions based on facial expressions, body expressions or voice intonation are not sensitive to people's age, gender and culture (Rani & Sarkar, 2006). This non-independence of users can invalidate generalization and can also lead to erroneous emotion recognition.

Still regarding facial expressions, although they give important clues about emotions (Busso et al., 2004) recognition based on these input signals may be compromised in the presence of a beard or mustache, when accessories are used on the face (e.g. glasses) or when there are changes in light intensity, problems in image quality, position, or human movement (Cruz et al., 2015) (H. Wang et al., 2010) (Chang et al., 2012) (Lai, Ramanathan, & Wechsler, 2008). In the case of spoken expression, recognition systems may see their performance affected because of noise from the surrounding area or the distance between people and sound capture devices (Sim et al., 2007). Finally, body posture is easy to imitate and varies from person to person (Basu et al., 2016).

In order to improve the performance and stabilization of emotional recognition systems, some researchers combine different types of input data (Park, Ryu, Sohn, & Cho, 2007). For example, Sebe et al. (Sebe et al., 2006) and Busso et al. (Busso et al., 2004) jointly use data related to facial and oral expression, and Gunes and Piccardi (Gunes & Piccardi, 2007) combines facial expression data with gestural data.

The most promising results considering the modalities under analysis (cf. facial expression, speaking, gesturing, and body posture), were achieved based on data collected from facial expression (Gunes & Piccardi, 2007). The most investigated modality is that related to facial expression. In contrast, gestural expression and body posture is the least explored modality (Castellano et al., 2007).

Looking at the same research now in aggregate (see table below), there are few papers that focus on emotion recognition based on data collection from multiple modalities simultaneously (Gunes & Piccardi, 2007) (Z. Zhang et al., 2016). Most of the multimodal approaches present in the literature combine the signals obtained from facial expression with oral (Pantic, Sebe, Cohn, & Huang, 2005). There are few approaches that combine signals produced by body movement (Castellano et al., 2007) (Gunes & Piccardi, 2007) (Castellano et al., 2007), and even fewer combine some kind of body expression with signs from other contexts such as physiological or social, as happens in the MeToo project.

Recently started by Caballe, the MeToo project aims to improve eLearning platforms so that they can detect, represent, and adapt to learners' emotions. The author intended to combine several types of input signals: psychological questionnaires, facial and oral expressions, gestural expression and body posture, information about heart activity, skin, keyboard and mouse use, etc. (Caballe, 2015).

RESEARCH	EXPRESS FACIAL	EXPRESS ORAL	EXPRESS GESTURE AND POSTURE	OTHER
Perdiz et al. (Perdiz et al., 2017)	HEAD.			**(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG.
S. H. Lee et al. (S. H. Lee et al., 2016)	FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH).			

Eckert et al. (Eckert et al., 2016)	FACS, CAU, EYES, EYEBROWS, NOSE, and MOUTH.			
Matlovic et al. (Matlovic et al., 2016)	FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017)			**(A. CEREBRAL)** EEG. **(SKIN)** EDA. **(PSYCHOSOCIAL)** EMOTIONS.
Gogia et al. (Gogia et al., 2016)	HEAD.			**(A. CEREBRAL)** EEG.
Z. Zhang et al. (Z. Zhang et al., 2016)	HEAD and FACS.			**(A. CARDÍACA)** BP(SBP, DBP), HR and PR. **(A. RESPIRATORY)** RESP(RR). **(SKIN)** EDA and ST. **(PSYCHOSOCIAL)** EMOTIONS.
Adams & Robinson (Adams & Robinson, 2015)	FACS (HEAD, EYES, EYEBROWS, EYELIDS, CHEEKS, WRINKLES, NOSE, LIPS, CHIN, JAW).			**(A. OCULAR)** GAZE.
Turan et al. (Turan et al., 2015)	FACE and EYES.			
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)		SPEECH and VOLUME.		
Lalitha et al. (Lalitha et al., 2015)		SPEECH, PITCH and VOLUME.		
Singh et al. (Singh et al., 2015)			SHOULDERS and HANDS.	
Saha et al. (Saha et al., 2014)			HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, and SPIN.	**(OTHER)** ACC.
Agrawal et al. (Agrawal et al., 2013)	EYES, MOUTH, LIPS, and SKIN.			
Soleymani et al. (Soleymani et al., 2013)	HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH.			**(A. CEREBRAL)** EEG. **(PSYCHOSOCIAL)** EMOTIONS.
Vermun et al. (Vermun et al., 2013)	HEAD, LIPS, MOUTH, and EYEBROWS.		ARMS, SHOULDERS, HIP, and KNEES.	
Yang & Bhanu (S. Yang & Bhanu, 2011)	HEAD and FACE.			
Dhall et al. (Dhall et al., 2011)	FACE.			
H. Wang et al. (H. Wang et al., 2010)	EYES.			
Gunes & Piccardi (Gunes & Piccardi, 2007)	LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD and JAW.		SHOULDERS, HANDS, FINGERS, FISTS, PALMS, and NECK.	
Castellano et al. (Castellano et al., 2007)			ARMS.	

Sebe et al. (Sebe et al., 2006)	HEAD, EYEBROWS, EYELIDS, and MOUTH.	VOLUME, SPEECH and PITCH.		
Busso et al. (Busso et al., 2004)	FOREHEAD, EYEBROWS, EYES and CHEEKS.	PITCH and VOLUME.		
Nwe et al. (Nwe et al., 2001)		SPEECH.		
L. S. Chen et al. (L. S. Chen et al., 1998)	EYES, EYEBROWS, MOUTH, WRINKLES, and FROWN.	SPEECH and PITCH.		

() represents a raw signal

2.2. PHYSIOLOGICAL CONTEXT VARIABLES

Machines are deaf and dumb i.e., they cannot use the natural modes of communication used by humans (Haritaoglu et al., 2001). Therefore, they also cannot directly identify emotions from expressions, and have to resort to collecting and classifying context data to infer how people feel.

Physiological signals are involuntary and tend to represent objective data points to be analyzed. Unlike body expression, they can function as partial indicators of affective states. Since many of these signals are possible to measure using sensors, their data can be interpreted by algorithms and classified into emotions (Rani & Sarkar, 2006). A physiological signal can be defined as the description of a physiological phenomenon regardless of the nature of the description (Nawasalkar et al., 2013) .

People may suppress the emotional content of nonverbal communication conveyed by body expression (Y. Liu et al., 2010) (K. H. Kim et al., 2004). However, the physiological impact of felt emotions is inevitable since the Autonomous Nervous System (ANS) is activated upon positive or negative arousal (Rani, Liu, Sarkar, & Vanman, 2006) causing instinctive and unconscious reactions in the human body at the level of brain, heart or respiratory activity (Van Der Vloed & Berentsen, 2009) (Jerritta et al., 2011) (Alzoubi et al., 2013) (S. Kim, Anh, & Thi, 2016), etc.

2.2.1. Brain activity

Brain activity is a widely used context variable in emotional detection systems. The choice of electroencephalogram **(EEG)** as input signal is related to the increase of research in the area of BCI (Y. Liu et al., 2010) and also with the fact that the literature establishes several times correlation between brain activity and emotions felt by people (Bos, 2010). For example, beta waves are typical in a relaxed but alert mental state and are most visible in the parietal and occipital lobes. High alpha activity has also been correlated with brain inactivation, making the beta/alpha ratio an important indicator of human arousal (Bos, 2010).

The data provided by the human brain are an important input in emotional detection systems, not least because the hypothalamus is responsible for processing the signals reaching the brain and triggering the respective physiological responses (e.g. increasing HR, activating the SCR response, etc.) (Kandel, Schwartz, & Jessell, 2000).

Despite its importance, the alpha component of the EEG increases with simple eye closure (Bos, 2010) and is influenced by facial muscle noise (e.g. eye blinking) or electrostatic artifacts caused by the presence of the various electrodes used in the collection (Bos, 2010) (Jerritta et al., 2011). In addition, the functioning of the human brain still needs further investigation. For example, researchers Niemic et al., Canli et al. and Jones argue that more activity in the left frontal region of the brain indicates a positive emotion, and more activity in the right anterior lobe area is related to a negative emotion (Niemic, Kirk, Brown, & Ph, 2002) (Canli, Desmond, Zhao, Glover, & Gabrieli, 1998) (Jones, 1992). However the papers by Y. Liu et al. and Lane et al. do not support these conclusions, even investigating the opposite hypotheses (Y. Liu et al., 2010) (R. D. Lane et al., 1997). There are several authors who use this signal as input for their systems. The following table summarizes the variables extracted in projects where the EEG signal is used.

RESEARCH	CONTEXT VARIABLES	
	BRAIN ACTIVITY	OTHER
Matlovic et al. (Matlovic et al., 2016)	EEG.	**Skin:** EDA. **(FACIAL EXP.)** FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017). **(PSYCHOSOCIAL)** EMOTIONS.
Gogia et al. (Gogia et al., 2016)	EEG.	**(FACIAL EXP.)** HEAD.
Sano & Eng (Sano & Eng, 2016)	EEG.	**Skin:** EDA and ST. **Muscle activity:** EMG. **Eye activity:** EOG. **Glandular activity:** MELAT. **(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL and SOCIAL. **(RECOGNIZED)** PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)** ACC and LIGHT.
Matiko et al. (Matiko et al., 2014)	EEG.	**(PSYCHOSOCIAL)** EMOTIONS.
Soleymani et al. (Soleymani et al., 2013)	EEG.	**(FACIAL EXP.)** HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH. **(PSYCHOSOCIAL)** EMOTIONS.
Murad & Malkawi (Murad & Malkawi, 2012)	EEG.	**Cardiac activity:** HR, HRV, PEP, SV and BP(SBP, DBP). **Respiratory activity:** RESP(VT, ROS, RR). **Skin:**

		EDA, nSRR and ST.
Bos (Bos, 2010)	EEG.	
Y. Liu et al. (Y. Liu et al., 2010)	EEG.	**(PSYCHOSOCIAL)** EMOTIONS.

() represents a raw signal

2.2.2. Cardiac activity

Cardiac activity can be measured through several instruments: electrocardiogram **(ECG)**; impedance cardiogram (**ICG)**; photoplethysmography (**PPG);** phonocardiogram **(PCG)**; etc. From these instruments it is possible to extract several context variables used in emotional detection systems: heart rate **(HR)**; heart rate variability (**HRV)** (obtained from ECG and PPG (K. H. Kim et al.)); pre-ejection period (**PEP)**; systolic volume (**SV)**; blood pressure or blood pressure (i.e. the pressure exerted by blood circulation on blood vessel walls, usually refers to blood pressure (Nawasalkar et al., 2013)) **(BP)**; systolic blood pressure (**SBP)**; diastolic blood pressure (**DBP)** (during each heartbeat the blood pressure varies between a maximum (systolic) and a minimum (diastolic) (Nawasalkar et al., 2013))**;** blood pressure with non-invasive collection **(NIBP)**; mean arterial pressure (**MAP)**; interbeat interval (**IBI)**; blood volume pulse (**BVP);** pulse rate (**PR);** root mean square of successive differences (**RMSSD)**; standard deviation the NN intervals (i.e. IBI) **(SDNN)**; left ventricular ejection time (**LVET)**; peripheral vascular resistance (**PVR); cardiac** output (**CO)**; vagal tone that mirrors vagus nerve activity (**VAGAL)**; and pulse wave time (time difference between a peak of the cardiac wave and the valley of the next pulse wave (Zenonos et al., 2016)) **(PTT)** or (PWTT) (Ahlstrom, Johansson, Uhlin, L?nne, & Ask, 2005) (Pollak & Obrist, 1983).

HR reflects emotional activity and has been used in conjunction with finger temperature to differentiate between positive and negative emotions (Mandryk & Atkins, 2007) (Winton, Putnam, & Krauss, 1984). For example, heart rate varies with fear and anger (S R Vrana, Cuthbert, & Lang, 1986) (Lisetti & Nasoz, 2004) and also with fright (Haag et al., 2004). HRV, usually calculated based on ECG, can also be estimated based on PPG (Alqaraawi, Alwosheel, & Alasaad, 2016) (Oura Crew, 2017) (Janković & Stojanović, 2017) (Fergus, n.d.) (Mayampurath, Volchenboum, & Sanchez-Pinto, 2018). HRV Reflects the changes between beats in HR or IBI (Mokhayeri & Toosizadeh, 2011) and is known to decrease with anxiety and increase with amusement (Murad & Malkawi, 2012) mental stress or frustration (Haag et al., 2004). It has already been used in studies to measure stress (Dishman et al., 2000) (Muaremi, Bexheti, Gravenhorst, Arnrich, & Tröster, 2014) for mental effort assessment (Calvert, 1998) and, in conjunction with EEG, as an indicator of attentional state (D. Chen & Vertegaal, 2004). PEP can be defined as the time between an ECG onset Q-wave and an ICG B-point (Stephens et al., 2010). It is known to increase with acute sadness, decrease with joy (Murad & Malkawi, 2012) and decrease with anger (R Sinha et al., 1992). SV, on the other hand, actively responds to negative emotions (e.g. decreases with grief, fear, and sadness) and remains unchanged to positive emotions (Kreibig, 2010). The BP measured for general health status assessment, varies with medication and physical activity, but also with emotions such as stress (R. Wang et al., 2014) fear and anger (Schwartz, Weinberger, & Singer, 1981) (Ax, 1953). The BP represents the pressure exerted by the circulation of blood on the walls of the blood vessels. With each heartbeat the BP varies between a maximum (i.e. SBP) and a minimum pressure value (i.e. DBP) (Nawasalkar et al., 2013). The increase in SBP is related to fear and anxiety (Murad & Malkawi, 2012) and increases with anger (R Sinha et al., 1992) (Schachter, 1957). DBP is known to increase with anger (R Sinha et al., 1992) anxiety and grief, and decrease with acute sadness (Kreibig, 2010). The NIBP allows continuous BP collection without the need to place pneumatic cuffs or other devices that only allow scalar (i.e. incomplete) collections (Solà i Carós, 2011). The IBI represents the interval between two consecutive heartbeats, it can be seen as another way to analyze HR (Zenonos et al., 2016) and its meaning is close to HRV (Kreibig, 2010). The BVP is an indicator related to stress (Jennifer a Healey et al., 2000) and allows measurement of heart activity (e.g. HR) (Jennifer a Healey et al., 2000). The PR represents the manual or sensor reading of HR on the wrist, finger, neck, etc. RMSSD is a measure of HRV and is used to determine vagal tone (Vrijkotte et al., 2000). It reflects the integrity of the vagus nerve, (a component linked to the autonomic control of the heart) and is associated with sudden death in epilepsy patients (DeGiorgio et al., 2010). Lee et al. in their emotion recognition research correlated RMSSD with fear (C. Lee et al., 2005). RMSSD is used in measuring the activity of the parasympathetic nervous system that controls the heart (Sztajzel, 2004). The SDNN is also a metric used in emotional recognition systems and refers to the standard deviation of interbeat intervals (i.e. IBI) (Zhao et al., 2016) and is a valid indicator of vagal tone (Electrophysiology, 1996a). LVET is the time that elapses between points B and X of the ICG (Stephens et al., 2010). It is important for assessing the performance of the left ventricle (Weissler, Harris, & Schoenfeld, 1969) and can be seen as a marker of cardiac stress (Sela, Shinar, & Tavakolian, 2016). LVET decreases with anger and with fear (R Sinha et al., 1992). The PVR represents the resistance to blood flow caused by vascular muscles and the diameter of blood vessels (Mosby's Medical Dictionary, 2009). An increase in PVR tends to reduce CO (Haddy, Overbeck, & Daugherty, 1968). PVR increases with fury (Schachter, 1957). Sadness causes a moderate increase in PVR and a decrease in CO (R Sinha et al., 1992). PTT has been related to stress (Fuke, 2013) (Zenonos et al., 2016) (Hey et al., 2009) and represents the time it takes for blood to flow between two arterial points (Gao, Olivier, & Mukkamala, 2016) (Gao, Olivier, & Mukkamala, 2016), i.e. the time it takes for a pulse wave to travel between two arterial points (e.g. from the aorta to the fingertips) (R. P. Smith, Argod, Pépin, & Lévy, 1999) (Murali et al., 2015).

There are several studies that collect data for emotional detection from cardiac activity. The following table summarizes some of the most important ones.

RESEARCH	CONTEXT VARIABLES	
	CARDIAC ACTIVITY	OTHER
Z. Zhang et al. (Z. Zhang et al., 2016)	BP(SBP, DBP), HR and PR.	**Respiratory activity:** RESP(RR). **Skin:** EDA and ST. **(FACIAL EXP.)** HEAD and FACS. **(PSYCHOSOCIAL)** EMOTIONS.
Zhao et al. (Zhao et al., 2016)	ECG(HR)*, HR and IBI(RMSSD, SDNN). * signal collected for comparison of HR data achieved by the device created by the author.	**Respiratory activity:** RR. **(PSYCHOSOCIAL)** EMOTIONS.
Zenonos et al. (Zenonos et al., 2016)	ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT).	**Skin:** ST. **(PSYCHOSOCIAL)** MOOD and EMOTIONS.

		(OTHER) ACC.
Basu et al. (Basu et al., 2016)	ECG, HR and PR.	**Respiratory activity:** RESP(RR). **Skin:** EDA and ST. **Muscle activity:** EMG.
Murali et al. (Murali et al., 2015)	ECG and ICG(PEP, PTT) and NIBP.	**Respiratory activity:** RESP(RR). **Skin:** EDA.
Kusserow et al. (Kusserow et al., 2013)	ECG(HR), HR and HR(HRV). * several experiments with different ways of collecting HR.	**Skin:** EDA and ST. **(PSYCHOSOCIAL)** MOOD and STRESS. **(OTHER)** ACC.
Alzoubi et al. (Alzoubi et al., 2013)	ECG(HRV).	**Respiratory activity:** RESP. **Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Nawasalkar et al. (Nawasalkar et al., 2013)	NIBP.	**Respiratory activity** RESP(RR).
Murad & Malkawi (Murad & Malkawi, 2012)	HR, HRV, PEP, SV and BP(SBP, DBP).	**Brain activity:** EEG. **Respiratory activity:** RESP(VT, ROS, RR). **Skin:** EDA, nSRR and ST.
C. Y. Chang et al. (Chang et al., 2012)	ECG, PR and BVP.	**Skin:** EDA. **(PSYCHOSOCIAL)** EMOTIONS.
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	ECG(HRV) and PPG.	**Eye activity:** PUPIL.
Setz et al. (Setz et al., 2010)	ECG*. **signals recorded but not used;*	**Respiratory activity:** RESP*. **Skin:** EDA.
J. Kim & Andre (J. Kim & André, 2008)	ECG(HR, HRV).	**Respiratory activity:** RESP(RR, Breathing Rate Variability (BRV)). **Skin:** EDA. **Muscle activity:** EMG.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	ECG(HR, HRV, IBI).	**Respiratory activity:** RESP(RR, RDEP). **Skin:** EDA and ST. **Muscle activity:**

		EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	ECG(HR, IBI).	**Skin:** EDA. **Eye activity:** PUPIL.
Mandryk & Atkins (Mandryk & Atkins, 2007)	ECG(HR).	**Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Zhai & Barreto (Zhai & Barreto, 2006)	BVP(IBI).	**Skin:** EDA and ST. **Eye activity:** PUPIL. **(OTHER)** TEMP and LIGHT.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	ECG(HR, HRV).	**Respiratory activity:** RESP. **Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** STRESS.
Herbon et al. (Herbon et al., 2005)	HR.	**Skin:** EDA and ST. **Eye activity:** PUPIL. **(DEMOGRAPH)** AGE and GENDER. **(PSYCHOSOCIAL)** HEALTH and EMOTIONS. **(DAILY ROTATION)** TECHEXPERT.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	HR.	**Skin:** EDA and ST. **(DEMOGRAPH)** AGE, GENDER and ETHNICITY. **(PSYCHOSOCIAL)** EMOTIONS.
K. H. Kim et al. (K. H. Kim et al., 2004)	ECG(HR, HRV) and PPG.	**Skin:** EDA and ST. **(PSYCHOSOCIAL)** EMOTIONS.
Haag et al. (Haag et al., 2004)	PPG(BVP(HR)) and ECG(HR).	**Respiratory activity:** RESP. **Skin:** EDA and ST. **Muscle activity:** EMG.
Jennifer a Healey	PPG(BVP(HR)) and ECG(HR, HRV).	**Respiratory activity:**

(Jennifer a Healey et al., 2000)		RESP. **Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** STRESS.
Vrijkotte et al. (Vrijkotte et al., 2000)	BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD(VAGAL)).	**(DEMOGRAPH)** AGE. **(PSYCHOSOCIAL)** PERSON, STRESS, and MOOD. **(RECOGNIZED)** ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST. **(INTEGRATION)** CAFFEI, ALCOH, and SMOKING. **(OTHER)** ACC.
Ritz et al. (Ritz et al., 2000)	HR, BP(SBP, DBP).	**Respiratory activity:** ROS, RR and VT. **Skin:** EDA. **(PSYCHOSOCIAL)** EMOTIONS.
J. Healey & Picard (J. Healey & Picard, 1998)	PPG(BVP(HR)).	**Respiratory activity:** RESP. **Skin:** EDA. **Muscle activity:** EMG.
Rajita Sinha (Rajita Sinha, 1996)	ECG(HR) and BP(SBP, DBP).	**Skin:** EDA and ST. **Muscle activity:** EMG. **Eye activity:** EOG. **(PSYCHOSOCIAL)** EMOTIONS.
Scott R. Vrana (Scott R. Vrana, 1993)	ECG(HR).	**Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
R Rinha et al. (R Sinha et al., 1992)	ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP) and PCG.	**(PSYCHOSOCIAL)** EMOTIONS.

() represents a raw signal

2.2.3. Respiratory activity

Respiratory activity is used in psychological and psychophysiological assessment of people and its continuous monitoring can help in the prevention of lung and heart problems (Ravichandran et al., 2015). Breathing data is more accurate if it is calculated based on the analysis of the gases exchanged by the lungs. However, this data collection technique hinders people's daily activities (e.g. running, walking, driving, etc.) (Jennifer a Healey et al., 2000). Thus, it is usually replaced by the technique of measuring chest cavity expansion during breathing (Jennifer a Healey et al., 2000). Some authors also use impedance-based techniques to measure breathing (e.g. Nawasalkar et al. (Nawasalkar et al., 2013)).

There are several respiration-related variables **(RESP)** used by researchers in emotional detection systems: current volume (**VT)**; oscillatory resistance **(ROS)**; respiration frequency (**RR**) (Murad & Malkawi, 2012); and depth of breathing **(RDEP)** (Lichtenstein, Antje; Oehme, 2008) (calculation made by the author based on the amplitude of the RR signal).

Information about breathing is used in various contexts, from the study of sleep (Long, Fonseca, Foussier, Haakma, & Aarts, 2014). (Sano & Eng, 2016), of laughter (Fukumto & Nagamatsu, 2016), stress detection (J. A. Healey & Picard, 2005), emotional and physical health monitoring (Murali et al., 2015) and emotional evolution over time (Alzoubi et al., 2013). Negative emotions can alter breathing patterns, and intense and sudden stimuli can cause momentary interruptions in breathing (Jennifer a Healey et al., 2000) (Frijda, 1986) (J. Kim & Andre, 2008).

RR and RDEP are related to physical activity or emotional arousal. They are the most commonly used measures of the breathing modality by researchers and can influence other signals such as electromyography (EMG) and skin conductance (SCR), due to the strong relationship of breathing with cardiac function (J. Kim & André, 2008). For example, less deep RDEP and lower RR can signify relaxation, rest and tranquility (Frijda, 1986) while the deeper RDEP and higher RR may indicate excitement, fury, and sometimes joy (Haag et al., 2004). Fast breathing with low VT may indicate tension such as panic, fear or concentration (Haag et al., 2004). ROS increases with emotional states other than neutral (Ritz et al., 2000).

Among the studies that use these variables, the ones shown in the following table stand out.

RESEARCH	CONTEXT VARIABLES	
	BREATHING ACTIVITY	OTHER
Z. Zhang et al. (Z. Zhang et al., 2016)	RESP(RR).	<u>**Cardiac activity:**</u> BP(SBP, DBP), HR and PR. <u>**Skin:**</u> EDA and ST. **(FACIAL EXP.)** HEAD and FACS. **(PSYCHOSOCIAL)** EMOTIONS.
Zhao et al. (Zhao et al., 2016)	RESP.	<u>**Cardiac activity:**</u> ECG(HR), HR and IBI(RMSSD, SDNN). **(PSYCHOSOCIAL)** EMOTIONS.
Basu et al. (Basu et al., 2016)	RESP(RR).	<u>**Cardiac activity:**</u> ECG, HR and PR. <u>**Skin:**</u> EDA and ST. <u>**Muscle activity:**</u> EMG.
Murali et al. (Murali et al., 2015)	RESP(RR).	<u>**Cardiac activity:**</u> ECG and ICG(PEP, PTT) and NIBP. <u>**Skin:**</u> EDA.
Alzoubi et al.	RESP.	<u>**Cardiac activity:**</u>

(Alzoubi et al., 2013)		ECG(HRV). **Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Nawasalkar et al. (Nawasalkar et al., 2013)	RESP(RR).	**Cardiac activity:** NIBP.
Murad & Malkawi (Murad & Malkawi, 2012)	RESP(VT, ROS, RR).	**Brain activity:** EEG. **Cardiac activity:** HR, HRV, PEP, SV and BP(SBP, DBP). **Skin:** EDA, nSRR and ST.
Setz et al. (Setz et al., 2010)	RESP*. **signals recorded but not used;*	**Cardiac activity:** ECG*. **Skin:** EDA.
J. Kim & Andre (J. Kim & André, 2008)	RESP(RR, Breathing Rate Variability (BRV*)). ** author specific*	**Cardiac activity:** ECG(HR, HRV). **Skin:** EDA. **Muscle activity:** EMG.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	RESP(RR, RDEP).	**Cardiac activity:** ECG(HR, HRV, IBI). **Skin:** EDA and ST. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	RESP.	**Cardiac activity:** ECG(HR, HRV). **Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** STRESS.
Haag et al. (Haag et al., 2004)	RESP.	**Cardiac activity:** PPG(BVP(HR)) and ECG(HR). **Skin:** EDA and ST. **Muscle activity:** EMG.
Jennifer a Healey (Jennifer a Healey et al., 2000)	RESP.	**Cardiac activity:** PPG(BVP(HR)) and ECG(HR, HRV). **Skin:** EDA. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** STRESS.
Ritz et al. (Ritz et al., 2000)	ROS, RR and VT.	**Cardiac activity:** HR, BP(SBP, DBP).

		Skin: EDA. **(PSYCHOSOCIAL)** EMOTIONS.
J. Healey & Picard (J. Healey & Picard, 1998)	RESP.	**Cardiac activity:** PPG(BVP(HR)). **Skin:** EDA. **Muscle activity:** EMG.

() represents a raw signal

2.2.4. Skin

The **skin** is the largest organ of the human body and has important functions such as protection and regulation of body temperature (Silva, 2014). The **nonspecific** skin conductance response **(nSRR)** can be used to measure the moisture level of the skin. Electrodermal activity **(EDA)**, skin conductance response (SCR), electrodermal response (EDR) or galvanic skin response (GSR) are terms that refer to skin conductance (J. A. Healey & Picard, 2005) (Sano & Eng, 2016) (Boucsein, 2012). When a person is exposed to an arousing stimulus, the (electrical) conductive capacity of the skin increases momentarily (i.e. a peak occurs followed by an exponential decrease) (Jaques et al., 2015). This characteristic, measurable through sensors, is an important indicator of psychological or physiological arousal and is therefore an interesting variable in the process of emotional detection (Murad & Malkawi, 2012).

While EDA responses arise from events that function as external emotional stimuli, nSRR responses do not result from an external stimulus or motor activity, i.e., they are of unknown origin happening spontaneously (Christie, 1981) (IMotions, 2016) (Setz et al., 2010).

EDA is one of the most chosen variables by researchers in emotional detection, despite the fact that it can be influenced by external factors such as temperature (Chandler & Cornes, 2012). In addition to being collected through non-intrusive sensors, it is associated with the sympathetic nervous system (SNS) (Poh, Swenson, & Picard, 2010), making it difficult or impossible for users to manipulate it (Sano & Picard, 2013b). Skin conductance reflects sudomotor innervation and sweat gland activity that increase with SNS activity (S. Taylor et al., 2015) (Poh et al., 2010). Since the SNS is influenced by the hypothalamus and limbic system and these are emotion-related structures, it makes sense to consider AGE as an input signal in emotional inference systems (Jaques et al., 2015) (S. Taylor et al., 2015).

EDA increases with frustration (Lisetti & Nasoz, 2004) reacts to emotional arousal (Chandler & Cornes, 2012), to negative emotions (e.g. boredom) (Giakoumis et al., 2010) to interest (arousal) (Iwasaki, Miyaki, & Rekimoto, 2010) and has a strong correlation with fun (Mandryk & Atkins, 2007). The EDA is better suited to measure arousal (calm versus excited) than valence (negative versus positive) and is a good indicator of conflict situations because it denotes situations of fear and anger (Chandler & Cornes, 2012) (Khalfa, Isabelle, Jean-Pierre, & Manon, 2002). In addition to correlating linearly with arousal (Peter J. Lang, 1995) it also reflects cognitive activity (Mandryk & Atkins, 2007) (Boucsein, 2012).

Skin conductance is a variable used in several types of research: monitoring drivers on rural roads (Helander, 1978) pilot performance analysis (Wilson, 2002); quality of sleep (Sano &

Picard, 2013a); etc. (J. A. Healey & Picard, 2005). It is considered a bio marker of stress (Boucsein, 2012) (Jaques et al., 2015) (Sano & Picard, 2013b) and is used as input in many emotional sensing systems as shown in the following table. However, a change in conductance can also result from physical exercise, temperature changes, or excessive movement (S. Taylor et al., 2015) (W. Chen et al., 2014) (Jaques et al., 2015) (Haag et al., 2004). Thus, in order to discriminate these situations from those resulting from SNS activity, researchers combine the collection of EDA with skin temperature **(ST)**, room temperature (TEMP) and the accelerometer (ACC). However, there are other ways to deal with the problem: Taylor et al. developed a machine learning algorithm that automatically detects EDA artifacts, an algorithm that has since been used by Sano et al. and Jaques et al. in their investigations (S. Taylor et al., 2015) (Sano & Eng, 2016) (Jaques et al., 2015).

The variation in ST happens because of blood flow as a result of vascular resistance and blood pressure (K. H. Kim et al., 2004). Although it can also be influenced by external factors (Haag et al., 2004), it is also an important variable in emotional detection on its own. For example, ST increases during sleep (Sano & Eng, 2016) (Martinez-Nicolas, Ortiz-Tudela, Rol, & Madrid, 2013a), increases more with anger than with fear (Levenson, Ekman, & Friesen, 1990), and than with joy (P. Ekman, R. W. Levenson, 1983).

ST should not be confused with core body temperature (CBT) (Sano & Eng, 2016). A decrease in CBT is usually preceded by an increase in ST (Sarabia, Rol, Mendiola, & Madrid, 2008) and during the circadian cycle there are times when the behavior of both is reversed (Gradisar & Lack, 2004) (Č, Škoda, Krbal, & Wasserbauer, 2016). For some time, CBT has been recognized as a reliable marker of the circadian cycle (Aschoff, 1983).

There are several types of research that correlate ST with other variables: classifying the awake/sleeping state (Sano & Picard, 2014); studying the happiness of students (Jaques et al., 2015); investigating insomnia and circadian rhythm (Lack, Gradisar, Van Someren, Wright, & Lushington, 2008) (Martinez-Nicolas, Ortiz-Tudela, Rol, & Madrid, 2013b) stress assessment (Kataoka et al., 1998) classify emotions (Murad & Malkawi, 2012) (Levenson et al., 1990) (Lisetti & Nasoz, 2004), etc.

The following table summarizes some of the research that considers EDA and ST in their systems.

RESEARCH	CONTEXT VARIABLES	
	SKIN	OTHER
Matlovic et al. (Matlovic et al., 2016)	EDA.	<u>**Brain activity:**</u> EEG. **(FACIAL EXP.)** FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017). **(PSYCHOSOCIAL)** EMOTIONS.
Z. Zhang et al. (Z. Zhang et al., 2016)	EDA and ST.	<u>**Cardiac activity:**</u> BP(SBP, DBP), HR and PR. <u>**Respiratory activity:**</u> RESP(RR). **(FACIAL EXP.)** HEAD and FACS. **(PSYCHOSOCIAL)** EMOTIONS.
Sano & Eng	EDA and ST.	<u>**Brain activity:**</u>

(Sano & Eng, 2016)		EEG. **Muscle activity:** EMG. **Eye activity:** EOG. **Glandular activity:** MELAT. **(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL and SOCIAL. **(RECOGNIZED)** PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)** ACC and LIGHT.
Zenonos et al. (Zenonos et al., 2016)	ST.	**Cardiac activity:** ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT). **(PSYCHOSOCIAL)** MOOD and EMOTIONS. **(OTHER)** ACC.
Basu et al. (Basu et al., 2016)	EDA and ST.	**Cardiac activity:** ECG, HR and PR. **Respiratory activity:** RESP(RR). **Muscle activity:** EMG.
Murali et al. (Murali et al., 2015)	EDA.	**Cardiac activity:** ECG and ICG(PEP, PTT) and NIBP. **Respiratory activity:** RESP(RR).
Jaques et al. (Jaques et al., 2015)	EDA and ST.	**(INTERACTION)** CALL, SMS and SOCIAL. **(RECOGNIZED)** ACADCL, ACADST and PHYSI. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(PSYCHOSOCIAL)** SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM and HAPPY. **(DAILY ROTATION)** LOCAL and SCREEN. **(OTHER)** ACC.
Kusserow et al. (Kusserow et al., 2013)	EDA and ST.	**Cardiac activity:** ECG(HR), HR and HR(HRV). **(PSYCHOSOCIAL)** MOOD and STRESS. **(OTHER)** ACC.

Alzoubi et al. (Alzoubi et al., 2013)	EDA.	**Cardiac activity:** ECG(HRV). **Respiratory activity:** RESP. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Sano & Picard (Sano & Picard, 2013b)	EDA.	**(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS. **(DAILY ROTATION)** LOCAL, SCREEN and ELECTR. **(INTERACTION)** CALL and SMS. **(INTEGRATION)** ALCOH and CAFFEI. **(OTHER)** ACC.
Murad & Malkawi (Murad & Malkawi, 2012)	EDA, nSRR and ST.	**Brain activity:** EEG. **Cardiac activity:** HR, HRV, PEP, SV and BP(SBP, DBP). **Respiratory activity:** RESP(VT, ROS, RR).
C. Y. Chang et al. (Chang et al., 2012)	EDA.	**Cardiac activity:** ECG, PR and BVP. **(PSYCHOSOCIAL)** EMOTIONS.
Hernandez et al. (Hernandez et al., 2011)	EDA.	**(PSYCHOSOCIAL)** STRESS. **(INTERACTION)** CALL.
Setz et al. (Setz et al., 2010)	EDA.	**Cardiac activity:** ECG*. **Respiratory activity:** RESP *. **signals recorded but not used;*
J. Kim & Andre (J. Kim & André, 2008)	EDA.	**Cardiac activity:** ECG(HR, HRV). **Respiratory activity:** RESP(RR, BRV). **Muscle activity:** EMG.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	EDA and ST.	**Cardiac activity:** ECG(HR, HRV, IBI). **Respiratory activity:** RESP(RR, RDEP). **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	EDA.	**Cardiac activity:** ECG(HR, IBI). **Eye activity:** PUPIL.
Mandryk & Atkins	EDA.	**Cardiac activity:**

(Mandryk & Atkins, 2007)		ECG(HR). **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.
Zhai & Barreto (Zhai & Barreto, 2006)	EDA, ST.	**Cardiac activity:** BVP(IBI). **Eye activity:** PUPIL. **(OTHER)** TEMP and LIGHT.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	EDA.	**Cardiac activity:** ECG(HR, HRV). **Respiratory activity:** RESP. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** STRESS.
Herbon et al. (Herbon et al., 2005)	EDA and ST.	**Cardiac activity:** HR. **Eye activity:** PUPIL. **(DEMOGRAPH)** AGE and GENDER. **(PSYCHOSOCIAL)** HEALTH and EMOTIONS. **(DAILY ROTATION)** TECHEXPERT.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	EDA and ST.	**Cardiac activity:** HR. **(DEMOGRAPH)** AGE, GENDER and ETHNICITY. **(PSYCHOSOCIAL)** EMOTIONS.
K. H. Kim et al. (K. H. Kim et al., 2004)	EDA and ST.	**Cardiac activity:** ECG(HR, HRV) and PPG. **(PSYCHOSOCIAL)** EMOTIONS.
Haag et al. (Haag et al., 2004)	EDA and ST.	**Cardiac activity:** PPG(BVP(HR)) and ECG(HR). **Respiratory activity:** RESP. **Muscle activity:** EMG.
Jennifer a Healey (Jennifer a Healey et al., 2000)	EDA.	**Cardiac activity:** PPG(BVP(HR)) and ECG(HR, HRV). **Respiratory activity:** RESP. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** STRESS.
Ritz et al. (Ritz et al., 2000)	EDA.	**Cardiac activity:** HR, BP(SBP, DBP).

		Respiratory activity: ROS, RR and VT. **(PSYCHOSOCIAL)** EMOTIONS.
J. Healey & Picard (J. Healey & Picard, 1998)	EDA.	**Cardiac activity:** PPG(BVP(HR)). **Respiratory activity:** RESP. **Muscle activity:** EMG.
Rajita Sinha (Rajita Sinha, 1996)	EDA and ST.	**Cardiac activity:** ECG(HR) and BP(SBP, DBP). **Muscle activity:** EMG. **Eye activity:** EOG. **(PSYCHOSOCIAL)** EMOTIONS.
Scott R. Vrana (Scott R. Vrana, 1993)	EDA.	**Cardiac activity:** ECG(HR). **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.

() represents a raw signal

2.2.5. Muscle activity

Muscle activity has been used in distinguishing between positive and negative emotions (Mandryk & Atkins, 2007). Electromyogram **(EMG)** is a method used in the diagnosis of nerve and muscle problems, and is based on the reading of electrical voltages upon muscle contraction (Jennifer a Healey et al., 2000) (J. Kim & André, 2008) (Lichtenstein, Antje; Oehme, 2008). EMG can be measured at the skin surface by placing sensors over the muscle area (e.g. (J. Healey & Picard, 1998) e (Haag et al., 2004)); or intramuscular through the use of small needles (e.g. (McNulty W, Gevirtz R, Berkoff G, 1994)) (Chandler & Cornes, 2012).

Some research related to emotion detection uses EMG on the face for valence determination, collecting information from the zygomatic (corners of the mouth) and corrugator (eyebrows) muscles (Lichtenstein, Antje; Oehme, 2008)(Lichtenstein, Antje; Oehme, 2008), because these are the most representative of emotional expressions (Perdiz et al., 2017) more precisely the valence component (Partala et al., 2005). For example, smiling and frowning can be recognized through EMG, allowing to distinguish between positive and negative valence (Mandryk & Atkins, 2007) (Partala et al., 2005). Researcher Sloan used surface EMG to measure zygomatic and corrugator activity in order to distinguish smiling from frowning (Sloan, 2004) .

In the face of fright the human body reacts with sweat in the palm of the hand, increased RR and HR, dryness in the mouth, and it also reacts with increased muscle tension which is measurable through EMG (Haag et al., 2004). Lower muscle activity in the eyebrow area in conjunction with higher activity in the cheek area, is related to mildly positive emotions (Cacioppo, J.T., Berntson, G.G., Larsen, J.T., Poehlmann, K.M., Ito, 2000). EMG allows detection of startle (Haag et al., 2004) EMG correlates strongly with challenge (Mandryk & Atkins, 2007) and can discriminate disgust from anger (Lisetti & Nasoz, 2004).

EMG is used in several types of research: entertainment (Mandryk & Inkpen, 2004) (Mandryk, Atkins, & Inkpen, 2006); upper limb physical rehabilitation (L. Liu et al., 2017) (Ehrampoosh, Yousefi-koma, & Mohtasebi, 2016); occupational therapy for stroke survivors (Thielbar et al., 2016); etc. It is also used by some emotional detection systems as shown in the following table.

One of the disadvantages of the surface measured EMG signal is the noise caused by speech or coughing. The alternative is to use the intramuscular method. However, because it is an intrusive process, it may not be possible to apply in all realities. (Mandryk & Atkins, 2007).

RESEARCH	CONTEXT VARIABLES	
	MUSCLE ACTIVITY	OTHER
Perdiz et al. (Perdiz et al., 2017)	EMG.	**Eye activity:** EOG. **(FACIAL EXP.)** HEAD.
Sano & Eng (Sano & Eng, 2016)	EMG.	**Brain activity:** EEG. **Skin:** EDA and ST. **Eye activity:** EOG. **Glandular activity:** MELAT. **(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL and SOCIAL. **(RECOGNIZED)** PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)** ACC and LIGHT.
Basu et al. (Basu et al., 2016)	EMG.	**Cardiac activity:** ECG, HR and PR. **Respiratory activity:** RESP(RR). **Skin:** EDA and ST.
Alzoubi et al. (Alzoubi et al., 2013)	EMG.	**Cardiac activity:** ECG(HRV). **Respiratory activity:** RESP. **Skin:** EDA. **(PSYCHOSOCIAL)** EMOTIONS.
J. Kim & Andre	EMG.	**Cardiac activity:**

(J. Kim & André, 2008)		ECG(HR, HRV). **<u>Respiratory activity:</u>** RESP(RR, BRV). **<u>Skin:</u>** EDA.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	EMG.	**<u>Cardiac activity:</u>** ECG(HR, HRV, IBI). **<u>Respiratory activity:</u>** RESP(RR, RDEP). **<u>Skin:</u>** EDA and ST. **(PSYCHOSOCIAL)** EMOTIONS.
Mandryk & Atkins (Mandryk & Atkins, 2007)	EMG.	**<u>Cardiac activity:</u>** ECG(HR). **<u>Skin:</u>** EDA. **(PSYCHOSOCIAL)** EMOTIONS.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	EMG.	**<u>Cardiac activity:</u>** ECG(HR, HRV). **<u>Respiratory activity:</u>** RESP. **<u>Skin:</u>** EDA. **(PSYCHOSOCIAL)** STRESS.
Partala et al. (Partala et al., 2005)	EMG.	**(PSYCHOSOCIAL)** EMOTIONS.
Haag et al. (Haag et al., 2004)	EMG.	**<u>Cardiac activity:</u>** PPG(BVP(HR)) and ECG(HR). **<u>Respiratory activity:</u>** RESP. **<u>Skin:</u>** EDA and ST.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	EMG*. *Results reported elsewhere.*	**<u>Glandular activity:</u>** CORT. **(PSYCHOSOCIAL)** EMOTIONS.
Jennifer a Healey (Jennifer a Healey et al., 2000)	EMG.	**<u>Cardiac activity:</u>** PPG(BVP(HR)) and ECG(HR, HRV). **<u>Respiratory activity:</u>** RESP. **<u>Skin:</u>** EDA. **(PSYCHOSOCIAL)** STRESS.
J. Healey & Picard (J. Healey & Picard, 1998)	EMG.	**<u>Cardiac activity:</u>** PPG(BVP(HR)). **<u>Respiratory activity:</u>** RESP. **<u>Skin:</u>** EDA.
Rajita Sinha (Rajita Sinha, 1996)	EMG.	**<u>Cardiac activity:</u>** ECG(HR) and BP(SBP, DBP). **<u>Skin:</u>**

		EDA and ST. **<u>Eye activity:</u>** EOG. **(PSYCHOSOCIAL)** EMOTIONS.
Scott R. Vrana (Scott R. Vrana, 1993)	EMG.	**<u>Cardiac activity:</u>** ECG(HR). **<u>Skin:</u>** EDA. **(PSYCHOSOCIAL)** EMOTIONS.

() represents a raw signal

2.2.6. Eye activity

Although **eye activity** is involuntary it is not possible to determine people's emotional state solely based on their data (Perdiz et al., 2017).

The electrooculogram **(EOG)** monitors eye movement by analyzing the voltage difference between the cornea and the retina. The collection is done by placing electrodes on the eye area (J. Zhang et al., 2013). Based on EOG it is possible to measure vertical and horizontal eye movement, blink frequency, long closure rate, blink amplitude, speed and frequency of rapid eye movement (saccade), etc. (Morris & Miller, 1996).

Research related to emotion detection generally uses EOG in EEG noise removal processes (Bos, 2010) (Fatourechi, Bashashatiemail, Wardemail, & Birchemail, 2007). For this reason, EOG is most often found in multimodal correlation investigations (Perdiz et al., 2017). There are few studies that collect this signal with the direct aim of detecting emotions from it (Cruz et al., 2015).

Emotional recognition based on eye tracking can be quite useful for research that focuses its study on individuals with physical or psychological problems (Raudonis, 2013). For example, gaze shape, can be seen as an indicator of social anxiety disorders (Schulze, Renneberg, & Lobmaier, 2013).

In addition to noise removal, EOG is a context variable used in several research realities: studying fatigue during flight simulation (Morris & Miller, 1996) sleep investigation and classification of awake/sleeping state (Estrada et al., 2006) safety systems (Hossain, Huda, Rahman, & Ahmad, 2016); identification of ischemic stroke (Giri, Fanany, & Arymurthy, 2016); facial expression recognition (Cruz et al., 2015); etc.

The pupil **(PUPIL)** is used in emotional detection systems. However, eye movement and pupil size are different between people, and depend on emotional state, mental state, and cognitive load (Raudonis, 2013) (Aracena et al., 2016). In addition to these factors, the constant adaptation of the pupil to changing light and the noises caused by blinking and instantaneous eye movements (Aracena et al., 2016), represent a challenge to the application of algorithms on the signal (Raudonis, 2013). The pupil provides various context data: diameter (or size); velocity (and acceleration) (Raudonis, 2013); fixation; stimulus onset and offset (Babiker et al., 2013); and diameter change time (Kawai et al., 2013) (Babiker et al., 2013).

Gaze position **(GAZE)** is also collected by emotional inference systems (rapid eye movements are known in the literature as saccades). Per e.g. Aracena et al. monitor this signal in conjunction with PUPIL during color image viewing to recognize emotions (Aracena et al., 2016).

The spontaneity of the pupil diameter reaction makes it a good input for an emotional detection system (Babiker et al., 2013). It mirrors the user's attention (Kawai et al., 2013), it correlates well with valence (Herbon et al., 2005) (Kawai et al., 2013), with emotional arousal (Aracena et al., 2016) (Partala & Surakka, 2003) (Margaret M. Bradley et al., 2008), and grows with increasing interest (Murai, Nakayama, & Shimizu, 1998).

Hess et al. showed in their research that when emotions are provoked by unpleasant images, the pupil tends to decrease in size, and when the images are pleasant the pupil dilates (Hess & Polt, 1960). However, more recently, Kawai et al. and Babiker et al. concluded the opposite (Kawai et al., 2013) (Babiker et al., 2013), and Partala et al. concluded that the pupil is larger with positive and negative stimuli compared to the neutral state (Partala & Surakka, 2003).

There are several investigations that use their pupil context data in their systems: form of alternative communication (e.g. with people who cannot move their head and arms) (Kawai et al., 2013); stress (Raudonis, 2013); etc. Perhaps the reason for choosing the pupil as the input signal is related to the fact that it belongs to the autonomic nervous system (ANS) (Matsunaga, 1990) (Aracena et al., 2016) (Aracena et al., 2016) or because it is a simple method that does not require the attachment of sensors to achieve good accuracy and reliability (Babiker et al., 2013).

The following table shows some investigations where the EOG and PUPIL variables are considered for emotional detection.

RESEARCH	CONTEXT VARIABLES	
	EYE ACTIVITY	OTHER
Perdiz et al. (Perdiz et al., 2017)	EOG.	**Muscle activity:** EMG. **(FACIAL EXP.)** HEAD.
Sano & Eng (Sano & Eng, 2016)	EOG.	**Brain activity:** EEG. **Skin:** EDA and ST. **Muscle activity:** EMG. **Glandular activity:** MELAT. **(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL and SOCIAL. **(RECOGNIZED)** PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)**

		ACC and LIGHT.
Aracena et al. (Aracena et al., 2016)	PUPIL and GAZE.	
Cruz et al. (Cruz et al., 2015)	EOG.	*Part of a developing system for emotion recognition that encompasses the signals (cf. EEG, EOG, EMG, and EDA).*
Raudonis (Raudonis, 2013)	EYES, GAZE, and PUPIL.	
Kawai et al. (Kawai et al., 2013)	PUPIL.	**(PSYCHOSOCIAL)** EMOTIONS.
Babiker et al. (Babiker et al., 2013)	EYES, GAZE, and PUPIL.	**(PSYCHOSOCIAL)** EMOTIONS.
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	PUPIL.	**Cardiac activity:** ECG(HRV) and PPG.
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	PUPIL.	**Cardiac activity:** ECG(HR, IBI). **Skin:** EDA.
Zhai & Barreto (Zhai & Barreto, 2006)	PUPIL.	**Cardiac activity:** BVP(IBI). **Skin:** EDA and ST. **(OTHER)** TEMP and LIGHT.
Herbon et al. (Herbon et al., 2005)	PUPIL.	**Cardiac activity:** HR. **Skin:** EDA and ST. **(DEMOGRAPH)** AGE and GENDER. **(PSYCHOSOCIAL)** HEALTH and EMOTIONS. **(DAILY ROTATION)** TECHEXPERT.
Partala & Surakka (Partala & Surakka, 2003)	PUPIL.	**(PSYCHOSOCIAL)** EMOTIONS.
R Rinha et al. (R Sinha et al., 1992)	EOG.	**Cardiac activity:** ECG(HR) and BP(SBP, DBP). **Skin:** EDA and ST. **Muscle activity:** EMG. **(PSYCHOSOCIAL)** EMOTIONS.

() represents a raw signal

2.2.7. Glandular activity

Glandular activity is also used in emotional detection systems (Omar, 2006). Cortisol **(CORT)** is produced by the adrenal glands (pituitary and adrenal gland) and secretion is controlled by the hypothalamus (Hormone Health Network, 2016). Cortisol is important for people's physical and psychological health (Dickerson & Kemeny, 2004). It serves to support the body in balancing sugar and blood pressure levels, and is important in the process of reducing inflammation and for the immune system (Frazão, 2016a). CORT levels vary during the day because they are related to physical activity and serotonin (SEROT). They can be measured through a blood, urine, or saliva sample (Frazão, 2016a) and from hair (Gow, Thomson, Rieder, Van Uum, & Koren, 2010.

CORT is known as the stress regulatory hormone (Smeets, Dziobek, & Wolf, 2009) (Kirschbaum, Pirke, & Hellhammer, 1993) (Ellenbogen, Schwartzman, Stewart, & Walker, 2002) (Dickerson & Kemeny, 2004). There are several types of research that analyze CORT activation: studies related to social aggression (Terburg, Morgan, & van Honk, 2009); mood state (van Eck et al., 2005); memory quality (Buchanan & Lovallo, 2001); attention levels (Ellenbogen et al., 2002); circadian cycle study (Boudreau, Dumont, Kin, Walker, & Boivin, 2011); etc.

The activation of CORT happens in the face of negative situations such as fear of a threat, chance of failure, or hindrance of reaching goals (Blascovich & Tomaka, 1996) (Dienstbier, 1989). For example, mental calculation, academic examinations, and public speaking can increase CORT levels because they act as psychological stressors (Kirschbaum et al., 1993) (Biondi & Picardi, 1999) (Dickerson & Kemeny, 2004) (Smeets et al., 2009). However, the various existing research suggests that the same stressful events may not trigger the same CORT changes in people (Mason, 1968) (Mason, 1968), highlighting the differences and uniqueness of each human being at the psychological and physiological level.

Melatonin **(MELAT)** is a natural hormone produced by the brain's pineal gland to regulate the body's biological rhythm and can be measured from blood or saliva (Salimetrics, n.d.) (Frazão, 2016b). MELAT is the largest naturally produced antioxidant (Markho, 2016), and allows the body to adapt to new time zones or new work shifts. Because it regulates sleep and sleep correlates with mood (mood), the circadian cycle is indirectly important for emotional sensing systems (Sano & Eng, 2016). MELAT is known as the sleep hormone (Markho, 2016).

The relationship of MELAT to the circadian cycle and sleep is well understood by the many investigations that exist in the area: Lewy et al. (Lewy & Sack, 1989); Sano et al. (Sano & Eng, 2016); Gil et l. (Gil, Aubert, & Beersma, 2014); Curcio et al. (Curcio et al., 2016); Sugiura et al. (Sugiura, Eto, Takada, & Kinoshita, 2016); Boudreau et al. (Boudreau et al., 2011); Lee et al. (Y. C. Lee, Chou, Fang, & Huang, 2011); etc. MELAT is also studied in other types of investigations: effect of Wi-Fi signal exposure on MELAT production (Markho, 2016); relationship with breast cancer (Hermida, Halberg, & Chavarria, 1988); study of the effect of colors on brain activity (Sroykham, Promraksa, Wongsathikun, & Wongsawat, 2015); etc.

Melatonin production depends on the alternation between daylight and darkness at night (Č et al., 2016) (Sroykham & Wongsawat, 2013). It usually starts a few hours before the usual bedtime and ends with the onset of brightness (Sano & Eng, 2016), but it is also possible that its secretion happens only after the onset of sleep (Č et al., 2016). The best sleep happens when core body temperature (CBT) decreases and melatonin increases (Č et al., 2016).

Light functions as a training factor for the sleep period in the circadian cycle of the human body (Czeisler et al., 1986) (Sano & Eng, 2016). For this reason, several researchers are studying the impact of artificial light from electronic devices on sleep (when used before bedtime). The light emanating from monitors causes a decrease in MELAT, increasing the level of alertness and decreasing the feeling of sleepiness (Curcio et al., 2016) (Sroykham & Wongsawat, 2013) (Czeisler et al., 1986). However Sugiura et al. argued the opposite, i.e. that the inhibition of comfortable sleep after reading a book on the tablet does not result from suppression of MELAT secretion but from other factors (Sugiura et al., 2016).

Serotonin **(SEROT)** is related to well-being and pleasure (Source, 2015) (Frazão, 2016a). It is also produced by the pineal gland and is known as the mood hormone (Markho, 2016). It implies mood and cognition (Merens, Willem Van der Does, & Spinhoven, 2007) And can be measured from a blood or urine sample (Visser et al., 2011) (Source, 2015).

Lower presence of SEROT in the body is related to depression, apathy, and psychiatric disorders (Markho, 2016). Increased through drugs in depressed people can improve mood (Moskowitz, Pinard, Zuroff, Annable, & Young, 2001). For example, people with violent behavior (e.g. convicted of violent crimes, arsonists, etc.) have lower rates of SEROT in their bodies (Virkkunen, 1994). When treated with drugs to increase SEROT they reduce aggressiveness (Fuller, 1996) (Virkkunen, 1994).

SEROT therefore plays an important role in the affective and social behavior of humans (C J Harmer et al., 2003). It increases feelings of dominance (assertiveness), decreases hostility (Moskowitz et al., 2001), increases cooperation in problem solving situations, reduces feelings of negative affect (Knutson et al., 1998) facilitates decision making (Merens et al., 2007), etc.

The pineal gland is responsible for balancing between SEROT and MELAT. During the night it produces MELAT to promote sleep, and during the day it increases the production of SEROT (Markho, 2016). SEROT is present with several investigations related to emotional processing (Merens et al., 2007): mood (mood) (Merens et al., 2007); depression (C J Harmer et al., 2003) anxiety (Catherine J. Harmer, Shelley, Cowen, & Goodwin, 2004); etc. However, it is also present in other types of research: impact of Wi-Fi signal on SEROT production (Markho, 2016); aggression (Knutson et al., 1998) (Moskowitz et al., 2001); social interactions and dominance (Moskowitz et al., 2001); childhood shyness (Battaglia et al., 2005) emotional disturbance (C J Harmer et al., 2003); etc.

The following table shows some investigations where the CORT, MELAT and SEROT variables are used for emotional detection.

RESEARCH	CONTEXT VARIABLES	
	GLANDULAR ACTIVITY	OTHER
Sano & Eng (Sano & Eng, 2016)	MELAT.	**<u>Brain activity:</u>** EEG. **<u>Skin:</u>** EDA and ST. **<u>Muscle activity:</u>** EMG. **<u>Eye activity:</u>** EOG. **(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL and SOCIAL. **(RECOGNIZED)**

		PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)** ACC and LIGHT.
Van Eck et al. (van Eck et al., 2005)	CORT.	**(PSYCHOSOCIAL)** LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS and EMOTIONS. **(RECOGNIZED)** PHYSI. **(INTEGRATION)** SMOKING, FOOD, CAFFEI and ALCOH.
C J Harmer et al. (C J Harmer et al., 2003)	SEROT. *Facial recognition did not involve technological means.*	**(PSYCHOSOCIAL)** MOOD, ENERGY, ANXIETY and EMOTIONS.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	CORT.	<u>**Muscle activity:**</u> EMG*. **(PSYCHOSOCIAL)** EMOTIONS. **Results reported elsewhere.*

() represents a raw signal

2.2.8. Analysis

Emotions affect the cardiovascular, respiratory, electrodermal, and muscular systems (Basu et al., 2016). Although they are of a more subjective and complex nature, the impossibility of manipulation of physiological signals by people makes them a good input for an emotional detection system due to the fact that they are shielded from social masking (K. H. Kim et al., 2004) (J. Kim & André, 2008). Moreover, it is possible to collect them in real time without people having to express themselves, thus broadening the scope of application (e.g. sick people, workers operating machinery, etc.) (Rani & Sarkar, 2006) (Poole & Ball, 2005).

However, despite recent advances in sensor technology (Wu, Batalin, Au, Bui, & Kaiser, 2007), there is still a need to increase the accuracy and diversity of collected data. In addition, cross noise between signals poses a challenge in collecting and processing context information (e.g. muscle noise present in EEG possible to detect through EOG and EMG) (Soleymani et al., 2013). The presence of artifacts can lead to distortion of the interpretation of the original signal (Coburn & Moreno, 1988). The obstructive nature of the collection is also a problem. It may pose restrictions on movement and discomfort in use, it may be impossible to use for long periods of time, it may interfere with other signals (e.g. heat generation may activate sweating), etc. (Tran et al., 2007) (Barea, Boquete, Rodriguez-Ascariz, Ortega, & López, 2011). Although there are advances in technology for more discreet and non-obstructive collection (Wu et al., 2008) (Wu et al., 2007), there is still a way to go towards miniaturization, portability, and wireless communication.

There can also be problems in generalization because of user dependence. The physiological reaction to an event is not the same between people (e.g. stressors act differently between individuals) (Manuck, Cohen, Rabin, Muldoon, & Bachen, 1991). Perhaps the individual subjective perception of each specific situation is the main determinant in the pattern of psychoendocrine response (Biondi & Picardi, 1999). A firefighter will be more accustomed to dealing with trauma. Faced with an accident, his body will react differently than, for example, a teacher. A young person may be more susceptible to shame than an adult. People who live in continued conflict zones will find it easier to deal with weapons and death.

Looking at the same investigations in aggregate (see table below), there are many investigations that collect physiological data for emotion recognition. However, most focus on analyzing data related to heart, respiratory, brain, and skin activity, and few use multiple modalities as input into their systems simultaneously (e.g. Chandler et al. correlates muscle and skin signals with facial expression data (Chandler & Cornes, 2012), Sano et al. correlates skin data with accelerometer, social activity, and personal data (Sano & Picard, 2013b)).

With the emergence of more sensors with higher reading accuracy, and devices with large computing power, more research is expected in the area of emotion detection, correlating variables from various modalities, with the goal of increasing the accuracy of emotion recognition systems (Gogia et al., 2016).

RESEARCH	VARIABLES OF PHYSIOLOGICAL CONTEXT							
	ACTIVITY **CEREBRAL**	ACTIVITY **CARDÍACA**	ACTIVITY **RESPIRAT.**	**SKIN**	ACTIVITY **MUSCULAR**	ACTIVITY **OCULAR**	ACTIVITY **GLANDULAR**	**OTHER**
Perdiz et al. (Perdiz et al., 2017)					EMG.	EOG.		**(FACIAL EXP.)** HEAD.
Matlovic et al. (Matlovic et al., 2016)	EEG.			EDA.				**(FACIAL EXP.)** FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017). **(PSYCHOSOCIAL)** EMOTIONS.
Gogia et al. (Gogia et al., 2016)	EEG.							**(FACIAL EXP.)** HEAD.
Z. Zhang et al. (Z. Zhang et al., 2016)		BP(SBP, DBP), HR and PR.	RESP(RR).	EDA and ST.				**(FACIAL EXP.)** HEAD and FACS. **(PSYCHOSOCIAL)** EMOTIONS.
Sano & Eng (Sano & Eng, 2016)	EEG.			EDA and ST.	EMG.	EOG.	MELAT.	**(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS**.** **(INTERACTION)** CALL, SMS, EMAIL and SOCIAL. **(RECOGNIZED)**

								PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)** ACC and LIGHT.
Zhao et al. (Zhao et al., 2016)		ECG(HR)*, HR and IBI(RMSSD, SDNN).	RESP.					**(PSYCHOSOCIAL)** EMOTIONS.
Zenonos et al. (Zenonos et al., 2016)		ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT).		ST.				**(PSYCHOSOCIAL)** MOOD and EMOTIONS. **(OTHER)** ACC.
Basu et al. (Basu et al., 2016)		ECG, HR and PR.	RESP(RR).	EDA and ST.	EMG.			
Aracena et al. (Aracena et al., 2016)						PUPIL and GAZE.		
Murali et al. (Murali et al., 2015)		ECG and ICG(PEP, PTT) and NIBP.	RESP(RR).	EDA.				
Jaques et al. (Jaques et al., 2015)				EDA and ST.				**(PSYCHOSOCIAL)** SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM and HAPPY. **(DAILY ROTATION)** LOCAL and SCREEN. **(INTERACTION)** CALL, SMS and SOCIAL. **(RECOGNIZED)** ACADCL, ACADST and PHYSI. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS. **(OTHER)** ACC.
Cruz et al. (Cruz et al., 2015)						EOG.		
Matiko et al. (Matiko et al., 2014)	EEG.							**(PSYCHOSOCIAL)** EMOTIONS.
Soleymani et al. (Soleymani et al., 2013)	EEG.							**(FACIAL EXP.)** HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH. **(PSYCHOSOCIAL)** EMOTIONS.

Kusserow et al. (Kusserow et al., 2013)		ECG(HR), HR and HR(HRV). .		EDA and ST.				**(PSYCHOSOCIAL)** MOOD and STRESS. **(OTHER)** ACC.
Alzoubi et al. (Alzoubi et al., 2013)		ECG(HRV) .	RESP.	EDA.	EMG.			**(PSYCHOSOCIAL)** EMOTIONS.
Nawasalkar et al. (Nawasalkar et al., 2013)		NIBP.	RESP(R R).					
Sano & Picard (Sano & Picard, 2013b)				EDA.				**(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS. **(DAILY ROTATION)** LOCAL, SCREEN and ELECTR. **(INTERACTION)** CALL and SMS. **(INTEGRATION)** ALCOH and CAFFEI. **(OTHER)** ACC.
Raudonis (Raudonis, 2013)						EYES, GAZE, and PUPIL.		
Kawai et al. (Kawai et al., 2013)						PUPIL.		**(PSYCHOSOCIAL)** EMOTIONS.
Babiker et al. (Babiker et al., 2013)						EYES, GAZE, and PUPIL.		**(PSYCHOSOCIAL)** EMOTIONS.
Murad & Malkawi (Murad & Malkawi, 2012)	EEG.	HR, HRV, PEP, SV and BP(SBP, DBP).	RESP(V T, ROS, RR).	EDA, nSRR and ST.				
C. Y. Chang et al. (Chang et al., 2012)		ECG, PR and BVP.		EDA.				**(PSYCHOSOCIAL)** EMOTIONS.
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)		ECG(HRV) and PPG.				PUPIL.		
Hernandez et al. (Hernandez et al., 2011)				EDA.				**(PSYCHOSOCIAL)** STRESS. **(INTERACTION)** CALL.
Bos (Bos, 2010)	EEG.							
Y. Liu et al. (Y. Liu et al., 2010)	EEG.							**(PSYCHOSOCIAL)** EMOTIONS.
Setz et al. (Setz et al., 2010)				EDA.				
J. Kim & Andre		ECG(HR, HRV).	RESP(R R, BRV).	EDA.	EMG.			

(J. Kim & André, 2008)								
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)		ECG(HR, HRV, IBI).	RESP(RR, RDEP).	EDA and ST.	EMG.			**(PSYCHOSOCIAL)** EMOTIONS.
Margaret M. (Margaret M. Bradley et al., 2008)		ECG(HR, IBI).		EDA.		PUPIL.		
Mandryk & Atkins (Mandryk & Atkins, 2007)		ECG(HR).		EDA.	EMG.			**(PSYCHOSOCIAL)** EMOTIONS.
Zhai & Barreto (Zhai & Barreto, 2006)		BVP(IBI).		EDA and ST.		PUPIL		**(OTHER)** TEMP and LIGHT.
J. A. Healey (J. A. Healey & Picard, 2005)		ECG(HR, HRV).	RESP.	EDA.	EMG.			**(PSYCHOSOCIAL)** STRESS.
Herbon et al. (Herbon et al., 2005)		HR.		EDA and ST.		PUPIL.		**(DEMOGRAPH)** AGE and GENDER. **(PSYCHOSOCIAL)** HEALTH and EMOTIONS. **(DAILY ROTATION)** TECHEXPERT.
Partala et al. (Partala et al., 2005)					EMG.			**(PSYCHOSOCIAL)** EMOTIONS.
Van Eck et al. (van Eck et al., 2005)							CORT.	**(PSYCHOSOCIAL)** LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS and EMOTIONS. **(RECOGNIZED)** PHYSI. **(INTEGRATION)** SMOKING, FOOD, CAFFEI and ALCOH.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		HR.		EDA and ST.				**(DEMOGRAPH)** AGE, GENDER and ETHNICITY. **(PSYCHOSOCIAL)** EMOTIONS.
K. H. Kim et al. (K. H. Kim et al., 2004)		ECG(HR, HRV) and PPG.		EDA and ST.				**(PSYCHOSOCIAL)** EMOTIONS.
Haag et al. (Haag et al., 2004)		PPG(BVP(HR)) and ECG(HR).	RESP.	EDA and ST.	EMG.			
Partala & Surakka (Partala & Surakka, 2003)						PUPIL.		**(PSYCHOSOCIAL)** EMOTIONS.

C J Harmer et al. (C J Harmer et al., 2003)							SEROT.	**(PSYCHOSOCIAL)** MOOD, ENERGY, ANXIETY, and EMOTIONS.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)					EMG.		CORT.	**(PSYCHOSOCIAL)** EMOTIONS.
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)		PPG(BVP(HR)) and ECG(HR, HRV).	RESP.	EDA.	EMG.			**(PSYCHOSOCIAL)** STRESS.
Vrijkotte et al. (Vrijkotte et al., 2000)		BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD(VAGAL)).						**(DEMOGRAPH)** AGE. **(PSYCHOSOCIAL)** PERSON, STRESS, and MOOD. **(RECOGNIZED)** ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST. **(INTEGRATION)** CAFFEI, ALCOH, and SMOKING. **(OTHER)** ACC.
Ritz et al. (Ritz et al., 2000)		HR, BP(SBP, DBP).	ROS, RR and VT.	EDA.				**(PSYCHOSOCIAL)** EMOTIONS.
J. Healey & Picard (J. Healey & Picard, 1998)		PPG(BVP(HR)).	RESP.	EDA.	EMG.			
Rajita Sinha (Rajita Sinha, 1996)		ECG(HR) and BP(SBP, DBP).		EDA and ST.	EMG.	EOG.		**(PSYCHOSOCIAL)** EMOTIONS.
Scott R. Vrana (Scott R. Vrana, 1993)		ECG(HR).		EDA.	EMG.			**(PSYCHOSOCIAL)** EMOTIONS.
R Sinha et al. (R Sinha et al., 1992)		ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP) and PCG.						**(PSYCHOSOCIAL)** EMOTIONS.

() represents a raw signal

2.3. SOCIAL AND PSYCHOLOGICAL CONTEXT VARIABLES

Computers are socially ignorant (Pentland, 2005). They are seen as logical and rational tools that are soon incompatible with the irrational and illogical nature of human emotions (Rosalind W. Picard, 2000).

Measuring emotions is one of the biggest problems in affective science and the study of enjoyment. The multitude of factors that affect emotional state such as physiology, subjective experience, background, and behavior (Babiker et al., 2013), mean that emotions cannot be measured directly (Nawasalkar et al., 2013) because each person may react differently to the same emotional stimulus (Raudonis, 2013). How someone experiences an emotion varies depending on time and space, and social and cultural component, etc. (J. Kim & André, 2008) (Dong, Lepri, & Pentland, 2011).

Emotions are the foundation of human interaction (Basu et al., 2016). Man is a collective being and the emotions he feels influence and are influenced by his group life (Dickerson & Kemeny, 2004) (Ekman, 1989). For example, when faced with a task where personal performance is put to the test (e.g. public speaking, mental calculation, etc.), people feel threatened because of the assessment that may be made by others (Dickerson & Kemeny, 2004) causing an increase in CORT and, consequently, an increase in stress (Kirschbaum et al., 1993). However, humans are complex beings and can express emotions ambiguously. Sadness caused by failure may (or may not) lead to crying but, some people cry with happiness in reaction to a positive event, and others smile while experiencing a negative emotion (Basu et al., 2016). In this case, in the face of failure, smiling would not signify happiness but rather discomfort, disappointment, unease, or sadness (Ekman, 1989). This human ambiguity makes it very difficult to detect emotions just by analyzing data from a single modality (Basu et al., 2016), as do many investigations related to emotion detection (Z. Zhang et al., 2016).

Social context variables are considered in human-machine interaction (HCI) studies (e.g. (Pantic et al., 2005)), and also in investigations of the emotional realm: quality of life (J. L. Pais-Ribeiro, 1999) physical and psychological well-being (Heitzmann & Kaplan, 1988) (Hohaus & Berah, 1996) mood (Moturu, Khayal, Aharony, Pan, & Pentland, 2011); stress (Bogomolov et al., 2014) (Sano & Picard, 2013b); depression (George, Blazer, Hughes, & Fowler, 1989); joy and well-being (Seligman, 2011) general health (Madan, Cebrian, Moturu, Farrahi, & Pentland, 2012); study of social emotions and self-conscious emotions such as shame, jealousy, envy, embarrassment, pride, etc. (Hareli, Shlomo; Parkinson, 2017) (Burnett, Bird, Moll, Frith, & Blakemore, 2009) (Robbins & Parlavecchio, 2006) (Robins & Tracy, 2004); etc.

Social support is a concept in health psychology (Dunbar, Ford, & Hunt, 1998) and is an important determinant of well-being throughout the life course (Kahn & Antonucci, 1980). Social relationships are the main instigator of emotions (T. D. Kemper, 1978) (Lazarus & Launier, 1978) (T. P. Kemper, 1991) and emotions are responses to events in context (Arnold, 1970). Some result from actual social relationships, but others are the result of imagined or remembered relationships (T. D. Kemper, 1978).

An individual with social support is someone who has people they can trust, who like you, value you, and care about you (Sarason, Sarason, Shearin, & Pierce, 1987). The relationship of social support to health has been much discussed in the literature (Wallston, Devellis, & Devellis, 1983) (Heitzmann & Kaplan, 1988): inhibits the development of and supports recovery from illness (Sheldon Cohen & Herbert, 1996); relieves stress (distress) (Heitzmann & Kaplan, 1988) (Rodin & Salovey, 1989) (J. L. Pais-Ribeiro, 1999) (S Cohen & Wills, 1985); protects from depression (Peirce, Frone, Russell, Cooper, & Mudar, 2000); reduces the feeling of uneasiness (Sarason, Sarason, Potter, & Antoni, 1985); increases life satisfaction (Hohaus & Berah, 1996); may prevent the risk of mental disorders (Ornelas, 1996) (Kessler, Price, & Wortman, 1985) such as depression, anxiety, and suicide (Hawkley & Cacioppo, 2010); promotes healthy aging (Antonucci, 2001); etc.

There are several authors who study social support. Kahn and Antonucci have argued that every human being is surrounded by a personal network of people in which there is given and received social support whose quality and composition is shaped over time as a result of the interaction with factors of situational context (e.g. expectations and requests from family, work, or other roles played in the network), and personal context (e.g. age, personality, demographic characteristics, etc.). In the convoy model, Antonucci represents the set of relationships of the human being through a set of concentric circles. The innermost one represents the individual himself and the remaining three represent the convoy of relationships, that is, the people who are important at the level of social support, for that individual. The ordering of circles represents the proximity of the network members at a given moment in life, with the outermost one representing the most distant members. The innermost circle represents the individual's personal context, the next represents close family members and friends (e.g. spouse, children, etc.), followed by the circle representing the remaining family members and friends, and finally the circle representing neighbors, co-workers, supervisors, etc. (Kahn & Antonucci, 1980) (Antonucci, 2001).

Dunst et al, who divided the origin of social support into informal (i.e. interaction with family, friends, neighbors, associations, church, etc.) and formal (i.e. interaction with health services, physicians, social workers, etc.), also proposed a set of dimensions of social support with relevance to well-being: i) size of the social network (number of people who are part of the relationship group); ii) existence of particular (e.g. marriage) and general social relationships (e.g. clubs, associations, company); iii) frequency of contacts with network members; iv) need for social support expressed by himself/herself; v) support made available by network members (type and quantity); vi) congruence between the social support made available by the group and the one the individual needs; vii) use by the individual of the social support made available by the network; viii) confidence of the individual in obtaining social support when he/she needs it; ix) reciprocity, i.e. the balance between the support received and provided to the network; x) closeness felt toward the providers of social support; and xi) satisfaction, i.e. the utility felt by the individual of the social support received (Dunst & Trivette, C. M., 1990).

Weiss argued that an individual's different social relationships play various roles in social support: i) attachment provided by people close to him (e.g., spouse, family, and close friends); ii) social integration that characterizes the support provided by group activities; iii) opportunity for nurturance provided, e.g., by children; iv) reassurance of worth, recognition of competence (e.g., co-workers); v) reliable alliance provided by relatives; and vi) guidance (Weiss, 1974) (Fiori, Antonucci, & Cortina, 2006).

Pais Ribeiro, in the research that presents the scale of satisfaction with social support (ESSS) received, proposes four factors to characterize people's social support: i) satisfaction with friends, which measures the satisfaction with friendships; ii) intimacy, which considers the satisfaction with intimate social support (e.g. spouse); iii) satisfaction with family, which measures the satisfaction with social support provided by the family; and iv) social activities, which considers the satisfaction with social activities performed (J. L. Pais-Ribeiro, 1999).

Taking inspiration from Antonucci's convoy model of concentric circles (Kahn & Antonucci, 1980), the factors of Pais Ribeiro (J. L. Pais-Ribeiro, 1999), and other research in the area, it was decided to divide the input social context variables of emotional detection systems into domains and categories. The domains represent the proximity and social relevance of each variable, and the categorization results from a personal grouping of the different variables according to their nature, relevance and role in promoting the relationship with the other elements of the network.

The personal domain represents the individual's context and is composed of the demographic, psychosocial, and daily routine categories. The categories interaction, recognition, and integration represent the individual's given and received social support in the private, proximate, and public domains. We group the three domains into one (i.e. other domains) because their psychosocial context variables may be present across any relationship level within the network.

2.3.1. Personal domain (demographic, psychosocial and daily routine)

The personal domain represents the individual context of each person and encompasses the variable categories: **demographic** (miscellaneous personal information); **psychosocial** (miscellaneous subjective self-appraisal); and **daily routine** (information related to their daily tasks).

The demographic category includes the following variables: age **(AGE)**; gender (**GENDER)**; ethnicity (**ETHNICITY)**; race (**RACE);** who you live with **(LIVING)** (i.e. if you live alone, with family, friends, etc.); school year **(SCHOOLY)**; and field of study **(SCHOOLA)**.

The psychosocial category groups information related to: sleep (**SLEEP)** (e.g. time to wake up or go to bed, time to sleep and to try to fall asleep, number of sleep interruptions during the night, etc.); **naps** (**NAP)** (e.g. quantity and time); personality (**PERSON)**; subjective self-appraisal of health status **(HEALTH)**, mood (**MOOD)**, alertness (**ALERT),** tiredness (**TIRED),** stress (**STRESS),** happiness (**HAPPY),** energy (**ENERGY),** calmness (**CALM),** well-being (**WELLBEING)**, depression (**DEPRESSION),** anxiety (**ANXIETY),** and anger (**ANGER)**; emotions in general (**EMOTIONS)** (e.g. valence and arousal, positive or negative emotions, or perceived intensity of a closed list of emotions or of a particular emotion); existence of recent life-changing events **(LIFEEVENTS)** (e.g. death of a loved one, divorce, etc.); or complications in life (**DIFFICULTIES)** (e.g. problems at work or at home, money or family problems).

The daily routine category includes: location (**LOCAL)** (Global Position System (GPS) or Wireless Fidelity (WiFi)); time of use of devices via screen on/off (**SCREEN);** use of applications **(APPS)** (e.g. entertainment, productivity, time of use, etc.); use of web browsers **(BROWSER)**; use of electronic devices (**ELECTR)** (e.g. whether you use, last time using tablet, smartphone, television, computer, etc.); and experience with computers, internet, and technology in general **(TECHEXPERT)**.

The following table presents some of the research that uses variables from the demographic, psychosocial, and daily routines categories in their emotional recognition processes.

RESEARCH	PERSONAL DOMAIN			
	DEMOGRAPH.	PSYCHOSSOCIAL	ROT. DAILY ROT.	OTHER
Matlovic et al. (Matlovic et al., 2016)		EMOTIONS*.		**(FACIAL EXP.)** FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017) **(A. CEREBRAL)** EEG. **(SKIN)** EDA.
Z. Zhang et al.		EMOTIONS*.		**(FACIAL EXP.)**

(Z. Zhang et al., 2016)				HEAD and FACS. **(A. CARDÍACA)** BP(SBP, DBP), HR and PR. **(A. RESPIRATORY)** RESP(RR). **(SKIN)** EDA and ST. **(PSYCHOSOCIAL)** EMOTIONS.
Sano & Eng (Sano & Eng, 2016)	LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA.	PERSON, SLEEP*, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS* and ANXIETY.	LOCAL, SCREEN, and APPS.	**INTERACTION:** CALL, SMS, EMAIL, FTF and SOCIAL. **RECOGNIZE:** PHYSI, ACADDG, ACADCL and ACADGR. **INTEGRATION:** ACADEX, CAFFEI, ALCOH and DRUGS. **(A. CEREBRAL)** EEG. **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG. **(A. GLANDULAR)** MELAT. **(OTHER)** ACC and LIGHT.
Zhao et al. (Zhao et al., 2016)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HR)*, HR and IBI(RMSSD, SDNN). **(A. RESPIRATORY)** RESP.
Zenonos et al. (Zenonos et al., 2016)		MOOD** and EMOTIONS*. *** measured by the intensity of the emotions felt.*		**(A. CARDÍACA)** ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT). **(SKIN)** ST. **(OTHER)** ACC.
Jaques et al. (Jaques et al., 2015)		SLEEP, NAP, STRESS*, HEALTH*, ENERGY*, ALERT*, CALM and HAPPY*.	LOCAL and SCREEN.	**INTERACTION:** CALL, SMS and SOCIAL. **RECOGNIZE:** ACADCL, ACADST and PHYSI. **INTEGRATION:** ACADEX, CAFFEI, ALCOH and DRUGS. **(SKIN)** EDA and ST. **(OTHER)** ACC.
Matiko et al. (Matiko et al., 2014)		EMOTIONS*.		**(A. CEREBRAL)** EEG.
Bogomolov et al. (Bogomolov et al., 2014)		PERSON and STRESS.		**INTERACTION:** CALL, SMS and PROXIMITY. **(OTHER)** WEATHER.

Soleymani et al. (Soleymani et al., 2013)		EMOTIONS*.		**(FACIAL EXP.)** HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH. **(A. CEREBRAL)** EEG.
Kusserow et al. (Kusserow et al., 2013)		MOOD and STRESS*.		**(A. CARDÍACA)** ECG(HR), HR and HR(HRV). **(SKIN)** EDA and ST. **(OTHER)** ACC.
Alzoubi et al. (Alzoubi et al., 2013)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HRV). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
Sano & Picard (Sano & Picard, 2013b)		PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS.	LOCAL, SCREEN and ELECTR.	<u>**INTERACTION:**</u> CALL and SMS. <u>**INTEGRATION:**</u> ALCOH and CAFFEI. **(SKIN)** EDA. **(OTHER)** ACC.
Kawai et al. (Kawai et al., 2013)		EMOTIONS*.		**(A. OCULAR)** PUPIL.
Babiker et al. (Babiker et al., 2013)		EMOTIONS*.		**(A. OCULAR)** EYES, GAZE, and PUPIL.
LikamWa et al. (LiKamWa et al., 2013)		MOOD*.	APPS, BROWSER and LOCAL.	<u>**INTERACTION:**</u> SMS, EMAIL and CALL.
C. Y. Chang et al. (Chang et al., 2012)		EMOTIONS*.		**(A. CARDÍACA)** ECG, PR and BVP. **(SKIN)** EDA.
Bauer & Lukowicz (Bauer & Lukowicz, 2012)			LOCATION.	<u>**INTERACTION:**</u> PROXIMITY, CALL and SMS. **No ground-truth was collected because the experiment was done during the exam season.*
Hernandez et al. (Hernandez et al., 2011)		STRESS*.		<u>**INTERACTION:**</u> CALL. **(SKIN)** EDA.
N. Lane et al. (N. Lane et al., 2011)		SLEEP, DEPRESSION, and WELLBEING.	LOCATION.	<u>**RECOGNIZE:**</u> PHYSI. <u>**INTERACTION:**</u> TALK. **(OTHER)**

		Information produced by BeWell based on recharging times and quiet periods.		ACC.
Y. Liu et al. (Y. Liu et al., 2010)		EMOTIONS*.		**(A. CEREBRAL)** EEG.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HR, HRV, IBI)**.** **(A. RESPIRATORY)** RESP(RR, RDEP). **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG.
Mandryk & Atkins (Mandryk & Atkins, 2007)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HR)**.** **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)		STRESS*.		**(A. CARDÍACA)** ECG(HR, HRV)**.** **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
Herbon et al. (Herbon et al., 2005)	AGE and GENDER.	HEALTH and EMOTIONS*.	TECHEXPERT.	**(A. CARDÍACA)** HR. **(SKIN)** EDA and ST. **(A. OCULAR)** PUPIL.
Partala et al. (Partala et al., 2005)		EMOTIONS*.		**(A. MUSCULAR)** EMG.
Van Eck et al. (van Eck et al., 2005)		LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD*, WELLBEING, STRESS* and EMOTIONS.		**<u>RECOGNIZE:</u>** PHYSI. **<u>INTEGRATION:</u>** SMOKING, FOOD, CAFFEI and ALCOH. **(A. GLANDULAR)** CORT.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	AGE, GENDER and ETHNICITY.	EMOTIONS*.		**(A. CARDÍACA)** HR. **(SKIN)** EDA and ST.
K. H. Kim et al. (K. H. Kim et al., 2004)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HR, HRV) and PPG**.** **(SKIN)** EDA and ST.

Partala & Surakka (Partala & Surakka, 2003)		EMOTIONS*.		**(A. OCULAR)** PUPIL.
C J Harmer et al. (C J Harmer et al., 2003)		MOOD, ENERGY, ANXIETY and EMOTIONS*.		**(A. GLANDULAR)** SEROT.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)		EMOTIONS*.		**(A. MUSCULAR)** EMG. **(A. GLANDULAR)** CORT.
Jennifer a Healey (Jennifer a Healey et al., 2000)		STRESS*.		**(A. CARDÍACA)** PPG(BVP(HR)) and ECG(HR, HRV). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
Vrijkotte et al. (Vrijkotte et al., 2000)	AGE.	PERSON, STRESS* and MOOD.		<u>**RECOGNIZE:**</u> ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST. <u>**INTEGRATION:**</u> CAFFEI, ALCOH, and SMOKING. **(A. CARDÍACA)** BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD(VAGAL)). **(OTHER)** ACC.
Ritz et al. (Ritz et al., 2000)		EMOTIONS*.		**(A. CARDÍACA)** HR, BP(SBP, DBP). **(A. RESPIRATORY)** ROS, RR and VT. **(SKIN)** EDA.
Rajita Sinha (Rajita Sinha, 1996)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HR) and BP(SBP, DBP). **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG.
Scott R. Vrana (Scott R. Vrana, 1993)		EMOTIONS*.		**(A. CARDÍACA)** ECG(HR). **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
R Sinha et al. (R Sinha et al., 1992)		EMOTIONS*.		**(A. CARDÍACA)** ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP) and PCG.

() represents a raw signal
** probably used as ground truth in the evaluation*

2.3.2. Other domains (interaction, recognition and integration)

The other domains include the domains: private (first line relatives such as children and close friends); close (other relatives and friends); and public (neighbors, work or school colleagues, supervisors or teachers, etc.). The three domains are aggregated here into one (cf. other domains) because their categories are common, i.e., they can exist at any level of the network.

This grouping of domains includes categories that represent social support given and received: **interaction** (variables related to maintaining contact between network elements); **recognition** (characteristics or properties that other network elements interpret as a sign of prestige, skills, or qualities); and **integration** (social activities or behaviors acquired from the network or promoting integration between network elements).

The interaction category includes: phone calls **(CALL)**; traditional (**MAIL)** or electronic correspondence (**EMAIL)**; written messages **(SMS)** and face-to-face interactions (**FTF)**. This category also includes subjective information such as: self-assessment of the quality of social interactions **(SOCIAL)** throughout or at specific times of the day (e.g. positive or negative day from the social point of view, number of positive and negative interactions before going to sleep and with elements of which domain, etc.); conversation (**TALK)** detected by the smartphone (e.g. voice time); and also proximity interaction **(PROXIMITY)** recorded through the discovery of nearby devices (e.g. bluetooth), assuming that each of these devices belongs to another distinct person (Bauer & Lukowicz, 2012) (method used in the investigations of Eagle et al. (Eagle & Pentland, 2006), Weppner et al. (Weppner & Lukowicz, 2011), and Nicolai et al. (Nicolai & Kenn, 2007)).

The recognition category encompasses: academic achievement **(ACADGR)** (e.g. grades, diplomas, etc.); academic degree **(ACADDG)**; physical activity (**PHYSI)** (e.g. number of trips to the gym, number of steps, running time, etc.); weight (**WEIGHT);** height (**HEIGHT);** body mass index (**BMI)**; waist size (**WAIST);** working time (**WORKYEARS)** (i.e. time in active life); occupation (**JOB)**. Also included are variables that lead to the attainment of skills and, consequently, greater recognition: study time (**ACADST) (**e.g. number of periods, duration, etc.); and curricular academic activity **(ACADCL)** (e.g. number and time of classes); etc.

The integration category includes: information about food **(FOOD)**; alcohol consumption **(ALCOH)**; caffeinated beverages (**CAFFEI)**; cigarettes or cigars smoked **(SMOKING)** and drugs **(DRUGS) (**e.g. amount, time of last intake, etc.); and extracurricular academic activity **(ACADEX)** (e.g. number and total time).

The following table presents some of the research that uses variables from the categories interaction, recognition and integration, in their emotional detection processes.

RESEARCH	PRIVATE, NEAR AND PUBLIC DOMAIN			
	INTERACT	RECOGNIZED.	INTEGRATION	OTHER
Sano & Eng (Sano & Eng, 2016)	CALL, SMS, EMAIL, FTF and SOCIAL.	PHYSI, ACADDG, ACADCL and ACADGR.	ACADEX, CAFFEI, ALCOH and DRUGS.	**DEMOGRAPH:** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **PSYCHOSOCIAL:** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **ROT. DAILY:** LOCAL, SCREEN, and APPS.

				(A. CEREBRAL) EEG. **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG. **(A. GLANDULAR)** MELAT. **(OTHER)** ACC and LIGHT.
Jaques et al. (Jaques et al., 2015)	CALL, SMS and SOCIAL.	ACADCL, ACADST and PHYSI.	ACADEX, CAFFEI, ALCOH and DRUGS.	**PSYCHOSOCIAL:** SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM and HAPPY. **ROT. DAILY:** LOCAL and SCREEN. **(SKIN)** EDA and ST. **(OTHER)** ACC.
Bogomolov et al. (Bogomolov et al., 2014)	CALL, SMS and PROXIMITY.			**PSYCHOSOCIAL:** PERSON and STRESS. **(OTHER)** WEATHER.
Sano & Picard (Sano & Picard, 2013b)	CALL and SMS.		ALCOH and CAFFEI.	**PSYCHOSOCIAL:** PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS. **ROT. DAILY:** LOCAL, SCREEN and ELECTR. **(SKIN)** EDA. **(OTHER)** ACC.
LikamWa et al. (LiKamWa et al., 2013)	SMS, EMAIL and CALL.			**PSYCHOSOCIAL:** MOOD. **ROT. DAILY:** APPS, BROWSER and LOCAL.
Bauer & Lukowicz (Bauer & Lukowicz, 2012)	PROXIMITY, CALL and SMS.			**ROT. DAILY:** LOCATION.
Hernandez et al. (Hernandez et al., 2011)	CALL.			**PSYCHOSOCIAL:** STRESS. **(SKIN)** EDA.
N. Lane et al. (N. Lane et al., 2011)		PHYSI.	TALK.	**PSYCHOSOCIAL:** SLEEP, DEPRESSION, and WELLBEING. **ROT. DAILY:** LOCATION. **(OTHER)** ACC.

Van Eck et al. (van Eck et al., 2005)		PHYSI.	SMOKING, FOOD, CAFFEI and ALCOH.	**PSYCHOSOCIAL:** LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS and EMOTIONS. **(A. GLANDULAR)** CORT.
Vrijkotte et al. (Vrijkotte et al., 2000)		ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST.	CAFFEI, ALCOH, and SMOKING.	**DEMOGRAPH:** AGE. **PSYCHOSOCIAL:** PERSON, STRESS, and MOOD. **(A. CARDÍACA)** BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD(VAGAL)). **(OTHER)** ACC.

() represents a raw signal

2.3.3. Analysis

Positive social relationships have been identified throughout time and cultures as the most relevant factor for people's well-being (H. T. Reis, Gable, Keyes, & Haidt, 2003) confirming the importance of social background data for an emotional detection system.

Highlighting the influence of social support on people's health, the World Health Organization (WHO) defines health as the complete state of physical, social, and mental well-being (WHO, 2016). However, despite the importance of the social component as a determinant of health, it is difficult to reach a consensus on the best way to assess someone's social support (J. L. Pais-Ribeiro, 1999). Given the inexistence of a direct, precise and global way to measure it (J. L. Pais-Ribeiro, 1999) (Heitzmann & Kaplan, 1988), researchers collect context variables related to human behavior as a social being (Bauer & Lukowicz, 2012) for use as input in their systems.

In this context, the smartphone is widely used as a means to obtain context data to assess social support. This choice is related to the fact that these devices are already part of people's lives, allowing for a more accurate collection and observation of spontaneous behaviors (Rachuri, Mascolo, Rentfrow, & Longworth, 2010). In addition, there is no need to add more sensors to collect context data (Bauer & Lukowicz, 2012) and that only one application needs to be installed on your of-the-shelf smartphone (N. Lane et al., 2011) the additional effort for the user is almost nil since much of the data to be collected already exists on the device as a result of their usual social activity (e.g. CALL, SMS, EMAIL, etc.).

However, besides the fact that not all people use a smartphone (e.g. older people may have difficulties in manipulating them), there is also the need to consider the existence of noise in the collected data: there may be CALL, SMS and EMAIL, resulting from typing errors or inadvertent typing or advertising actions, referring to the technological challenge of analyzing oral and written content; the analysis of social interaction based on PROXIMITY may be misled by the discovery of multiple devices belonging to the same person on the network; the manipulation of the device may not be exclusive to one user considering leading to erroneous data about its use (e.g. BROWSER and APPs); etc.

On the other hand, many investigations use data collected from user questionnaires as input (e.g. ALERT, TIRED, etc.). The absence of other automatic inference mechanisms confers a certain degree of weakness to systems that use this subjective information as input to their systems (Muaremi, Arnrich, & Tröster, 2012). In addition, and given the confidential nature of the processed data, ethical issues may arise and there is, for example, the need to ensure the operation of the system without the need for persistence of the raw data collected (Rachuri et al., 2010) (N. Lane et al., 2011).

Looking at the investigations now presented in aggregate (see table below), there are few investigations that diversify psychosocial context data and there are also few that challenge correlations with data from other modalities.

RESEARCH	PERSONAL DOMAIN			PRIVATE, NEAR AND PUBLIC DOMAIN			OTHER
	DEMOGRAPH.	PSYCHOSSOCIAL	ROT. DAILY ROT.	INTERACT	RECOGNIZED.	INTEGRATION	
Matlovic et al. (Matlovic et al., 2016)		EMOTIONS.					**(FACIAL EXP.)** FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017) **(A. CEREBRAL)** EEG. **(SKIN)** EDA.
Z. Zhang et al. (Z. Zhang et al., 2016)		EMOTIONS.					**(FACIAL EXP.)** HEAD and FACS. **(A. CARDÍACA)** BP(SBP, DBP), HR and PR. **(A. RESPIRATORY)** RESP(RR). **(SKIN)** EDA and ST.
Sano & Eng (Sano & Eng, 2016)	LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA.	PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY.	LOCAL, SCREEN, and APPS**.**	CALL, SMS, EMAIL, FTF and SOCIAL.	PHYSI, ACADDG, ACADCL and ACADGR.	ACADEX, CAFFEI, ALCOH and DRUGS.	**(A. CEREBRAL)** EEG. **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG. **(A. GLANDULAR)** MELAT. **(OTHER)** ACC and LIGHT.
Zhao et al. (Zhao et al., 2016)		EMOTIONS.					**(A. CARDÍACA)** ECG(HR)*, HR and IBI(RMSSD, SDNN). **(A. RESPIRATORY)** RESP.
Zenonos et al. (Zenonos et al., 2016)		MOOD and EMOTIONS.					**(A. CARDÍACA)** ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT)**.** **(SKIN)** ST.

							(OTHER) ACC.
Jaques et al. (Jaques et al., 2015)		SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM and HAPPY.	LOCAL and SCREEN.	CALL, SMS and SOCIAL.	ACADCL, ACADST and PHYSI.	ACADEX, CAFFEI, ALCOH and DRUGS.	**(SKIN)** EDA and ST. **(OTHER)** ACC.
Matiko et al. (Matiko et al., 2014)		EMOTIONS.					**(A. CEREBRAL)** EEG.
Bogomolov et al. (Bogomolov et al., 2014)		PERSON and STRESS.		CALL, SMS and PROXIMITY.			**(OTHER)** WEATHER.
Soleymani et al. (Soleymani et al., 2013)		EMOTIONS.					**(FACIAL EXP.)** HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH. **(A. CEREBRAL)** EEG.
Kusserow et al. (Kusserow et al., 2013)		MOOD and STRESS.					**(A. CARDÍACA)** ECG(HR), HR and HR(HRV). **(SKIN)** EDA and ST. **(OTHER)** ACC.
Alzoubi et al. (Alzoubi et al., 2013)		EMOTIONS.					**(A. CARDÍACA)** ECG(HRV). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
Sano & Picard (Sano & Picard, 2013b)		PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS.	LOCAL, SCREEN and ELECTR.	CALL and SMS.		ALCOH and CAFFEI.	**(SKIN)** EDA. **(OTHER)** ACC.
Kawai et al. (Kawai et al., 2013)		EMOTIONS.					**(A. OCULAR)** PUPIL.
Babiker et al. (Babiker et al., 2013)		EMOTIONS.					**(A. OCULAR)** EYES, GAZE, and PUPIL.
LikamWa et al. (LiKamWa et al., 2013)		MOOD.	APPS, BROWSER and LOCAL.	SMS, EMAIL and CALL.			
C. Y. Chang et al.		EMOTIONS.					**(A. CARDÍACA)** ECG, PR and BVP. **(SKIN)**

(Chang et al., 2012)							EDA.
Bauer & Lukowicz (Bauer & Lukowicz, 2012)			LOCATION.	PROXIMITY, CALL and SMS.			
Hernandez et al. (Hernandez et al., 2011)		STRESS.		CALL.			**(SKIN)** EDA.
N. Lane et al. (N. Lane et al., 2011)		SLEEP, DEPRESSION, and WELLBEING.	LOCATION.	TALK.	PHYSI.		**(OTHER)** ACC.
Y. Liu et al. (Y. Liu et al., 2010)		EMOTIONS.					**(A. CEREBRAL)** EEG.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)		EMOTIONS.					**(A. CARDÍACA)** ECG(HR, HRV, IBI)**.** **(A. RESPIRATORY)** RESP(RR, RDEP). **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG.
Mandryk & Atkins (Mandryk & Atkins, 2007)		EMOTIONS.					**(A. CARDÍACA)** ECG(HR)**.** **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)		STRESS.					**(A. CARDÍACA)** ECG(HR, HRV) **(RESPIRATORY A.)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
Herbon et al. (Herbon et al., 2005)	AGE and GENDER.	HEALTH and EMOTIONS.	TECHEXPERT.				**(A. CARDÍACA)** HR. **(SKIN)** EDA and ST. **(A. OCULAR)** PUPIL.
Partala et al. (Partala et al., 2005)		EMOTIONS.					**(A. MUSCULAR)** EMG.
Van Eck et al. (van Eck et al., 2005)		LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD,			PHYSI.	SMOKING, FOOD, CAFFEI and ALCOH.	**(A. GLANDULAR)** CORT.

		WELLBEING, STRESS and EMOTIONS.					
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	AGE, GENDER and ETHNICITY.	EMOTIONS.					**(A. CARDÍACA)** HR. **(SKIN)** EDA and ST.
K. H. Kim et al. (K. H. Kim et al., 2004)		EMOTIONS.					**(A. CARDÍACA)** ECG(HR, HRV) and PPG**.** **(SKIN)** EDA and ST.
Partala & Surakka (Partala & Surakka, 2003)		EMOTIONS.					**(A. OCULAR)** PUPIL.
C J Harmer et al. (C J Harmer et al., 2003)		MOOD, ENERGY, ANXIETY and EMOTIONS.					**(A. GLANDULAR)** SEROT.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)		EMOTIONS.					**(A. MUSCULAR)** EMG. **(A. GLANDULAR)** CORT.
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)		STRESS.					**(A. CARDÍACA)** PPG(BVP(HR)) and ECG(HR, HRV). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
Vrijkotte et al. (Vrijkotte et al., 2000)	AGE.	PERSON, STRESS, and MOOD.			ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST.	CAFFEI, ALCOH, and SMOKING.	**(A. CARDÍACA)** BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD (VAGAL)). **(OTHER)** ACC.
Ritz et al. (Ritz et al., 2000)		EMOTIONS.					**(A. CARDÍACA)** HR, BP(SBP, DBP). **(A. RESPIRATORY)** ROS, RR and VT. **(SKIN)** EDA.
Rajita Sinha (Rajita Sinha, 1996)		EMOTIONS.					**(A. CARDÍACA)** ECG(HR) and BP(SBP, DBP)**.** **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG.

Scott R. Vrana (Scott R. Vrana, 1993)		EMOTIONS.					**(A. CARDÍACA)** ECG(HR)**.** **(SKIN)** EDA. **(A. MUSCULAR)** EMG.
R Sinha et al. (R Sinha et al., 1992)		EMOTIONS.					**(A. CARDÍACA)** ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP) and PCG.

() represents a raw signal

2.4. OTHER VARIABLES

This section presents variables used to support the noise treatment of other signals or less commonly used by automatic emotion detection systems.

Temperature **(TEMP)** and ambient light **(LIGHT)** are considered by some authors as masking variables (Martinez-Nicolas et al., 2013a) because they can influence other context data collected. TEMP can influence core body temperature (CBT) (Wakamura & Tokura, 2002) and, for this reason, is used by researchers to discriminate ST increase caused by emotional or environmental origin (Jaques et al., 2015) (Lisetti & Nasoz, 2004) (see page 33). TEMP is also used in research related to smart homes and well-being (Suryadevara, Member, & Mukhopadhyay, 2012). LIGHT has been used in studies related to well-being and in sleep (Sander, Markvart, Kessel, Argyraki, & Johnsen, 2015) (Sano & Eng, 2016) (Harb, Hidalgo, & Martau, 2014). Light can influence physiological signals such as HR (Scheer, van Doornen, & Buijs, 1999) and EEG (Cajochen, Zeitzer, Czeisler, & Dijk, 1999). It may reduce eye activity and the feeling of drowsiness because of lower MELAT production as a result of increased brightness (Scheer et al., 1999) (Cajochen et al., 1999).

Acceleration **(ACC)** allows recognizing physical activity such as walking, sitting, climbing chairs, counting steps (Jaques et al., 2015) (Sano & Eng, 2016), sleep patterns (Ancoli-Israel et al., 2003) (Sano & Eng, 2016), etc. ACC is also used by researchers to detect ST variations because of people's increased physical activity rather than emotional reaction (S. Taylor et al., 2015) (Jaques et al., 2015). However, ACC is also used directly for correlation in emotional detection systems: mood (Zenonos et al., 2016); stress (Garica-Ceja, Osmani, & Mayora, 2015) (Sano & Picard, 2013b) (Kusserow et al., 2013); etc.

Weather variations **(WEATHER)** are associated with mood problems (Denissen, Butalid, Penke, & van Aken, 2008) (Sanders & Brizzolara, 1982), sleep, fatigue, discontentment, (Faust, Weidmann, & Wehner, 1974), health (Sanders & Brizzolara, 1982), etc. WEATHER investigations use several meteorological variables: sunny weather; precipitation; wind; humidity; barometric pressure; etc. (Howarth & Hoffman, 1984) (Denissen et al., 2008) (Sanders & Brizzolara, 1982). WEATHER is also used by emotional detection research: stress (Bogomolov et al., 2014); mood (Howarth & Hoffman, 1984) (Denissen et al., 2008) (Sanders & Brizzolara, 1982) (Hardt & Gerbershagen, 1999); etc.

The following table presents some research that uses these variables in the emotional detection process.

RESEARCH	CONTEXT VARIABLES	
	OTHER	PREVIOUS
Sano & Eng (Sano & Eng, 2016)	ACC and LIGHT.	**(BRAIN ACTIVITY)** EEG. **(SKIN)** EDA and ST. **(MUSCLE ACTIVITY)** EMG. **(EYE ACTIVITY)** EOG. **(GLANDULAR ACTIVITY)** MELAT. **(DEMOGRAPH)**

		LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL, FTF and SOCIAL. **(RECOGNIZED)** PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS.
Zenonos et al. (Zenonos et al., 2016)	ACC.	**(CARDIAC ACTIVITY)** ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT). **(SKIN)** ST. **(PSYCHOSOCIAL)** MOOD and EMOTIONS.
Jaques et al. (Jaques et al., 2015)	ACC.	**(SKIN)** EDA and ST. **(PSYCHOSOCIAL)** SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM and HAPPY. **(DAILY ROTATION)** LOCAL and SCREEN. **(INTERACTION)** CALL, SMS and SOCIAL. **(RECOGNIZED)** ACADCL, ACADST and PHYSI. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS.
Saha et al. (Saha et al., 2014)	ACC.	**(GESTURE EXP. AND POST.)** HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, and SPIN.
Bogomolov et al. (Bogomolov et al., 2014)	WEATHER.	**(PSYCHOSOCIAL)** PERSON and STRESS. **(INTERACTION)** CALL, SMS and PROXIMITY.
Kusserow et al. (Kusserow et al., 2013)	ACC.	**(CARDIAC ACTIVITY)** ECG(HR), HR and HR(HRV). **(SKIN)** EDA and ST. **(PSYCHOSOCIAL)** MOOD and STRESS.
Sano & Picard (Sano & Picard, 2013b)	ACC.	**(SKIN)** EDA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS. **(DAILY ROTATION)** LOCAL, SCREEN and ELECTR. **(INTERACTION)** CALL and SMS. **(INTEGRATION)** ALCOH and CAFFEI.
N. Lane et al. (N. Lane et al., 2011)	ACC.	**(INTERACTION)** TALK. **(RECOGNIZED)**

		PHYSI. **(PSYCHOSOCIAL)** SLEEP, DEPRESSION, and WELLBEING. **(DAILY ROTATION)** LOCATION.
Zhai & Barreto (Zhai & Barreto, 2006)	TEMP and LIGHT.	**(CARDIAC ACTIVITY)** BVP(IBI). **(SKIN)** EDA and ST. **(EYE ACTIVITY)** PUPIL.
Vrijkotte et al. (Vrijkotte et al., 2000)	ACC.	**(CARDIAC ACTIVITY)** BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD(VAGAL)). **(DEMOGRAPH)** AGE. **(PSYCHOSOCIAL)** PERSON, STRESS, and MOOD. **(RECOGNIZED)** ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST. **(INTEGRATION)** CAFFEI, ALCOH, and SMOKING.

() represents a raw signal

2.5. ANALYSIS

The following table summarizes the context variables used by the investigations analyzed, now grouped by modality.

There are several investigations that focus on collecting data from facial expression, oral expression, and body posture to infer emotions, perhaps because it is essentially through nonverbal expression that humans communicate emotions (Singh et al., 2015) (Nawasalkar et al., 2013). However, the problems of generalization of systems caused by dependence on culture, gender, and age (Rani & Sarkar, 2006), the erraticity caused by the possible faking of the user (K. H. Kim et al., 2004) (L. S. Chen et al., 1998) (Chang et al., 2012), and the ambiguity in interpreting emotions from the way people express themselves nonverbally (e.g. crying for joy or smiling for shame) (Ekman, 1989), make this signal somewhat uninteresting for input to an emotional detection system.

As it is possible to see by analyzing the following table, there are many studies that resort to the collection of physiological context variables. The variables usually chosen by researchers for emotional detection are those that guarantee some rate of success (Lisetti & Nasoz, 2004). Typically, physiological context variables are chosen because there are already efficient sensors capable of measuring them objectively, and because the information originates from the autonomous nervous system (ANS), i.e., it cannot be triggered or manipulated intentionally (Jerritta et al., 2011) (Van Der Vloed & Berentsen, 2009). However the use of these signals as input also has disadvantages: the obstructiveness caused by the need to measure through sensors; the complexity of the task of mapping physiological patterns to specific emotions (J. Kim & André, 2008); and the need to predict and treat noise present in some signals (e.g. EMG and EOG in EEG) (Soleymani et al., 2013). Finally, to note the small number of investigations that use glandular activity data in their systems perhaps due to the intrusive nature of current methods of collecting urine, blood or saliva. However, the relationship of SEROT to well-being

(Source, 2015) of CORT with stress (Smeets et al., 2009) (Kirschbaum et al., 1993) (Ellenbogen et al., 2002) (Dickerson & Kemeny, 2004) and of MELAT with mood and alertness level (Sano & Eng, 2016) (Curcio et al., 2016), make these data into interesting signals for input to an emotional inference system. With the evolution of technology and emergence of non-intrusive sensors or hormone measurement methods, it can be expected that more research will make use of glandular information to automatically detect emotions.

The strength of the relationship of social support to well-being and overall health (Kahn & Antonucci, 1980) (Sarason et al., 1985) (Hohaus & Berah, 1996) (Heitzmann & Kaplan, 1988) (Seligman, 2011), make this signal an important input for emotion recognition systems. Perhaps because there is not yet an accepted way to measure social support (J. L. Pais-Ribeiro, 1999) (Heitzmann & Kaplan, 1988), there is a lack of diversification in the collection of psychosocial context data as can be seen in the visual analysis of the table below. It is the authors' conviction that the collection of more psychosocial context variables may contribute positively to the quality of emotional inference systems.

In the personal domain at the level of the demographic category there are other data whose correlation should be tested: marital status; practiced religion; active participation in political parties, associations or performance of important roles in society; love relationships (e.g. number of marriages or boyfriends, interval between relationships, etc.); children (ages, relationship, number of dependents living in the same house, dependents living in another house, financial dependence, dependents with special needs, etc.); absences and delays at work (due to illness, family assistance, etc.); overtime (i.e. supplementary work); vacations taken and not taken; credit obtained (e.g., quantity, value, and object (e.g., house, car, etc.)); ownership and type of housing (i.e., apartment, house, or farm); housing environment (city or country); distance to work; type of transportation to work; type of neighborhood; purchases made (number of purchases and value); etc. In the psychosocial category, other data can also be considered: self-assessment of the social support given and received; quality of the relationship in the different domains (cf. private, close, and public); feeling of loneliness and isolation; level of satisfaction and personal fulfillment with employment; willingness to change jobs or professions; work intensity; general assessment of the health of the members of the private domain; current and overcomed health complications (own and of the members of the private domain); self-assessment of their own and their children's happiness; optimism about the future and the children's financial independence; times of falling asleep and waking up, duration of the various sleep phases; etc. Other variables are also suggested for the daily routine category: drugs ingested (e.g. quantity, number of doses, active ingredient, etc.); time spent watching television, playing alone, reading for leisure, and in contact with nature; meals (daily number, food balance, type (i.e. meat, fish, vegetarian, other) and interval between meals); number of steps; gym (scheduled, completed, and missed visits); waking leisure (couch, bed, or table time); household activities (e.g. gardening, housekeeping, meal preparation); personal hygiene and dressing (time and number of times); etc.

In the other domains (cf. private, close and public), more specifically at the level of the interaction category, there is no correlation between variables that can represent contact between network members: face-to-face conversation; conversation through instant messaging (IM) (e.g. number of interactions received and carried out, by periods of the day, duration, type of addressees according to the domain they belong to, etc.); socializing with members of the private domain (e.g. time, regularity, etc.); visits to and from members of the network (e.g. number and time); entertainment (e.g. group games, outings, trips, visits to the mall and amusement parks, etc.); activity on social networks.); visits to and from network members (e.g. number and time); entertainment (e.g. group games, outings, trips, visits to the mall and amusement parks, etc.); activity on social networks; existence of informal love relationships (e.g. existence of colored friendships, use of dating tools, or participation in sexual diversification groups); quality of social interactions via CALL and SMS; number of characters and words in SMS; etc. In the recognition category there are also other variables that can influence the prestige recognized by the other elements of the network: participation in associations, political parties or religious groups; performance of important positions in companies, organizations or religion; social class; level of income earned; etc. Finally, at the level of the integration category, the authors also identify other variables that can assess integration in the group: diet to maintain or improve physical appearance; hobbies, smartphone (type, operating system, regularity of exchange); car or motorcycle (type, quantity, etc.); way of dressing; participation in cultural events; going to the movies; time outdoors; etc.

The inclusion of new and better sensors in smartphones, smartwatches, and other wearables will allow investigations to correlate more social context data and increase inference accuracy (Zenonos et al., 2016). However, more research is also needed to find ways to replace self-reply forms (e.g. ALERT, TIRED, ENERGY, CALM, etc.) with automatic inference methods from context information.

Finally, we also suggest other environmental context variables that can be considered for correlation in emotional detection systems: level of noise, humidity, light, temperature, O2 and CO2, while awake and during sleep; level of ultraviolet rays, humidity, atmospheric pressure, etc. outside the home.

Automatic emotion recognition is a challenge (Gunes & Piccardi, 2007) (L. S. Chen et al., 1998) because an emotion is a construct systematically produced by cognitive processes, subjective feelings, physiological arousal, motivational tendencies, and behavioral reactions (J. Kim & André, 2008). Despite the increased accuracy of emotion inference systems resulting from the diversification of context data sources (Bakhtiyari & Husain, 2014), the authors believe that correlation with social, cultural, and religious context data, could contribute positively to the accuracy of an emotion detection system. It is also our belief that emotions cannot be inferred just by collecting context data from a single modality. With increasing computational power and sensor technology, we can expect the number of multimodality investigations related to emotion detection to grow (Gogia et al., 2016). Trying to infer emotions solely based on physiological sensors, or on facial expression, oral expression, posture, etc., will be something very reductive of the true emotional meaning. Therefore, we consider it necessary to correlate data from various modalities including subjective context data (cf. social, cultural, religious, personal, etc.) in order to increase the reliability of emotional detection systems.

RESEARCH	EXP. FACIAL AND ORAL, AND BODY POSTURE	PHYSIOLOGICAL ENVIRONMENT	PSYCHOSOCIAL CONTEXT	OTHER VARIABLES
Perdiz et al. (Perdiz et al., 2017)	**(FACIAL EXP.)** HEAD.	**(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG.		
S. H. Lee et al.	**(FACIAL EXP.)**			

(S. H. Lee et al., 2016)	FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH).			
Eckert et al. (Eckert et al., 2016)	**(FACIAL EXP.)** FACS, CAU, EYES, EYEBROWS, NOSE, and MOUTH.			
Matlovic et al. (Matlovic et al., 2016)	**(FACIAL EXP.)** FaceReader (Noldus, 2017) and Shore (Fraunhofer IIS, 2017)	**(A. CEREBRAL)** EEG. **(SKIN)** EDA.	**(PSYCHOSOCIAL)** EMOTIONS.	
Gogia et al. (Gogia et al., 2016)	**(FACIAL EXP.)** HEAD.	**(A. CEREBRAL)** EEG.		
Z. Zhang et al. (Z. Zhang et al., 2016)	**(FACIAL EXP.)** HEAD and FACS.	**(A. CARDÍACA)** BP(SBP, DBP), HR and PR. **(A. RESPIRATORY)** RESP(RR). **(SKIN)** EDA and ST.	**(PSYCHOSOCIAL)** EMOTIONS.	
Sano & Eng (Sano & Eng, 2016)		**(A. CEREBRAL)** EEG. **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG. **(A. OCULAR)** EOG. **(A. GLANDULAR)** MELAT.	**(DEMOGRAPH)** LIVING, AGE, GENDER, ETHNICITY, RACE, SCHOOLY and SCHOOLA. **(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, HAPPY, ALERT, ENERGY, CALM, STRESS, and ANXIETY. **(DAILY ROTATION)** LOCAL, SCREEN, and APPS. **(INTERACTION)** CALL, SMS, EMAIL, FTF and SOCIAL. **(RECOGNIZED)** PHYSI, ACADDG, ACADCL and ACADGR. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS.	**(OTHER)** ACC and LIGHT.
Zhao et al. (Zhao et al., 2016)		**(A. CARDÍACA)** ECG(HR), HR and IBI(RMSSD, SDNN). **(A. RESPIRATORY)** RESP.	**(PSYCHOSOCIAL)** EMOTIONS.	
Zenonos et al. (Zenonos et al., 2016)		**(A. CARDÍACA)** ECG(HR(IBI(RMSSD, SDNN)), HRV) and PPG(PR, PTT). **(SKIN)** ST.	**(PSYCHOSOCIAL)** MOOD and EMOTIONS.	**(OTHER)** ACC.
Basu et al. (Basu et al., 2016)		**(A. CARDÍACA)** ECG, HR and PR. **(A. RESPIRATORY)** RESP(RR). **(SKIN)**		

		EDA and ST. **(A. MUSCULAR)** EMG.		
Aracena et al. (Aracena et al., 2016)		**(A. OCULAR)** PUPIL and GAZE.		
Adams & Robinson (Adams & Robinson, 2015)	**(FACIAL EXP.)** FACS (HEAD, EYES, EYEBROWS, EYELIDS, CHEEKS, WRINKLES, NOSE, LIPS, CHIN, JAW).	**(A. OCULAR)** GAZE.		
Turan et al. (Turan et al., 2015)	**(FACIAL EXP.)** FACE and EYES.			
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	**(EXP. ORAL)** SPEECH and VOLUME.			
Lalitha et al. (Lalitha et al., 2015)	**(EXP. ORAL)** SPEECH, PITCH and VOLUME.			
Singh et al. (Singh et al., 2015)	**(GESTURE EXP. AND POST.)** SHOULDERS and HANDS.			
Murali et al. (Murali et al., 2015)		**(A. CARDÍACA)** ECG and ICG(PEP, PTT) and NIBP**.** **(A. RESPIRATORY)** RESP(RR). **(SKIN)** EDA.		
Jaques et al. (Jaques et al., 2015)		**(SKIN)** EDA and ST.	**(PSYCHOSOCIAL)** SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM and HAPPY. **(DAILY ROTATION)** LOCAL and SCREEN. **(INTERACTION)** CALL, SMS and SOCIAL. **(RECOGNIZED)** ACADCL, ACADST and PHYSI. **(INTEGRATION)** ACADEX, CAFFEI, ALCOH and DRUGS.	**(OTHER)** ACC.
Cruz et al. (Cruz et al., 2015)		**(A. OCULAR)** EOG.		
Saha et al. (Saha et al., 2014)	**(GESTURE EXP. AND POST.)** HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, and SPIN.			**(OTHER)** ACC.
Matiko et al. (Matiko et al., 2014)		**(A. CEREBRAL)** EEG.	**(PSYCHOSOCIAL)** EMOTIONS.	

Bogomolov et al. (Bogomolov et al., 2014)			**(PSYCHOSOCIAL)** PERSON and STRESS. **(INTERACTION)** CALL, SMS and PROXIMITY.	**(OTHER)** WEATHER.
Agrawal et al. (Agrawal et al., 2013)	**(FACIAL EXP.)** EYES, MOUTH, LIPS, and SKIN.			
Soleymani et al. (Soleymani et al., 2013)	**(FACIAL EXP.)** HEAD, EYES, NOSE, EYEBROWS, LIPS, and MOUTH.	**(A. CEREBRAL)** EEG.	**(PSYCHOSOCIAL)** EMOTIONS.	
Vermun et al. (Vermun et al., 2013)	**(GESTURE EXP. AND POST.)** HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP, and KNEES.			
Kusserow et al. (Kusserow et al., 2013)		**(A. CARDÍACA)** ECG(HR), HR and HR(HRV). **(SKIN)** EDA and ST.	**(PSYCHOSOCIAL)** MOOD and STRESS.	**(OTHER)** ACC.
Alzoubi et al. (Alzoubi et al., 2013)		**(A. CARDÍACA)** ECG(HRV). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** EMOTIONS.	
Nawasalkar et al. (Nawasalkar et al., 2013)		**(A. CARDÍACA)** NIBP. **(A. RESPIRATORY)** RESP(RR).		
Sano & Picard (Sano & Picard, 2013b)		**(SKIN)** EDA.	**(PSYCHOSOCIAL)** PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED and STRESS. **(DAILY ROTATION)** LOCAL, SCREEN and ELECTR. **(INTERACTION)** CALL and SMS. **(INTEGRATION)** ALCOH and CAFFEI.	**(OTHER)** ACC.
Raudonis (Raudonis, 2013)		**(A. OCULAR)** EYES, GAZE, and PUPIL.		
Kawai et al. (Kawai et al., 2013)		**(A. OCULAR)** PUPIL.	**(PSYCHOSOCIAL)** EMOTIONS.	
Babiker et al. (Babiker et al., 2013)		**(A. OCULAR)** EYES, GAZE, and PUPIL.	**(PSYCHOSOCIAL)** EMOTIONS.	
LikamWa et al.			**(PSYCHOSOCIAL)** MOOD.	

(LiKamWa et al., 2013)			**(DAILY ROTATION)** APPS, BROWSER and LOCAL. **(INTERACTION)** SMS, EMAIL and CALL.	
Murad & Malkawi (Murad & Malkawi, 2012)		**(A. CEREBRAL)** EEG. **(A. CARDÍACA)** HR, HRV, PEP, SV and BP(SBP, DBP)**.** **(A. RESPIRATORY)** RESP(VT, ROS, RR). **(SKIN)** EDA, nSRR and ST.		
C. Y. Chang et al. (Chang et al., 2012)		**(A. CARDÍACA)** ECG, PR and BVP. **(SKIN)** EDA.	**(PSYCHOSOCIAL)** EMOTIONS.	
Bauer & Lukowicz (Bauer & Lukowicz, 2012)			**(DAILY ROTATION)** LOCATION. **(INTERACTION)** PROXIMITY, CALL and SMS.	
Yang & Bhanu (S. Yang & Bhanu, 2011)	**(FACIAL EXP.)** HEAD and FACE.			
Dhall et al. (Dhall et al., 2011)	**(FACIAL EXP.)** FACE.			
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)		**(A. CARDÍACA)** ECG(HRV) and PPG. **(A. OCULAR)** PUPIL.		
Hernandez et al. (Hernandez et al., 2011)		**(SKIN)** EDA.	**(PSYCHOSOCIAL)** STRESS. **(INTERACTION)** CALL.	
N. Lane et al. (N. Lane et al., 2011)			**(PSYCHOSOCIAL)** SLEEP, DEPRESSION, and WELLBEING. **(DAILY ROTATION)** LOCATION. **(INTERACTION)** TALK. **(RECOGNIZED)** PHYSI.	**(OTHER)** ACC.
H. Wang et al. (H. Wang et al., 2010)	**(FACIAL EXP.)** EYES.			
Bos (Bos, 2010)		**(A. CEREBRAL)** EEG.		
Y. Liu et al. (Y. Liu et al., 2010)		**(A. CEREBRAL)** EEG.	**(PSYCHOSOCIAL)** EMOTIONS.	

Setz et al. (Setz et al., 2010)		**(SKIN)** EDA.		
J. Kim & Andre (J. Kim & André, 2008)		**(A. CARDÍACA)** ECG(HR, HRV). **(A. RESPIRATORY)** RESP(RR, BRV). **(SKIN)** EDA. **(A. MUSCULAR)** EMG.		
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)		**(A. CARDÍACA)** ECG(HR, HRV, IBI). **(A. RESPIRATORY)** RESP(RR, RDEP). **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** EMOTIONS.	
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)		**(A. CARDÍACA)** ECG(HR, IBI). **(SKIN)** EDA. **(A. OCULAR)** PUPIL.		
Gunes & Piccardi (Gunes & Piccardi, 2007)	**(FACIAL EXP.)** LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD and JAW. **(GESTURE EXP. AND POST.)** SHOULDERS, HANDS, FINGERS, FISTS, PALMS, and NECK.			
Castellano et al. (Castellano et al., 2007)	**(GESTURE EXP. AND POST.)** ARMS.			
Mandryk & Atkins (Mandryk & Atkins, 2007)		**(A. CARDÍACA)** ECG(HR). **(SKIN)** EDA. **(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** EMOTIONS.	
Sebe et al. (Sebe et al., 2006)	**(FACIAL EXP.)** HEAD, EYEBROWS, EYELIDS, and MOUTH. **(EXP. ORAL)** VOLUME, SPEECH and PITCH.			
Zhai & Barreto (Zhai & Barreto, 2006)		**(A. CARDÍACA)** BVP(IBI). **(SKIN)** EDA and ST. **(A. OCULAR)** PUPIL.		**(OTHER)** TEMP and LIGHT.

J. A. Healey & Picard (J. A. Healey & Picard, 2005)		**(A. CARDÍACA)** ECG(HR, HRV)**.** **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** STRESS.	
Herbon et al. (Herbon et al., 2005)		**(A. CARDÍACA)** HR. **(SKIN)** EDA and ST. **(A. OCULAR)** PUPIL.	**(DEMOGRAPH)** AGE and GENDER. **(PSYCHOSOCIAL)** HEALTH and EMOTIONS. **(DAILY ROTATION)** TECHEXPERT.	
Partala et al. (Partala et al., 2005)		**(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** EMOTIONS.	
Van Eck et al. (van Eck et al., 2005)		**(A. GLANDULAR)** CORT.	**(PSYCHOSOCIAL)** LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS and EMOTIONS. **(RECOGNIZED)** PHYSI. **(INTEGRATION)** SMOKING, FOOD, CAFFEI and ALCOH.	
Busso et al. (Busso et al., 2004)	**(FACIAL EXP.)** FOREHEAD, EYEBROWS, EYES and CHEEKS. **(EXP. ORAL)** PITCH and VOLUME.			
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		**(A. CARDÍACA)** HR. **(SKIN)** EDA and ST.	**(DEMOGRAPH)** AGE, GENDER, and ETHNICITY. **(PSYCHOSOCIAL)** EMOTIONS.	
K. H. Kim et al. (K. H. Kim et al., 2004)		**(A. CARDÍACA)** ECG(HR, HRV) and PPG**.** **(SKIN)** EDA and ST.	**(PSYCHOSOCIAL)** EMOTIONS.	
Haag et al. (Haag et al., 2004)		**(A. CARDÍACA)** PPG(BVP(HR)) and ECG(HR). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA and ST. **(A. MUSCULAR)** EMG.		
Partala & Surakka (Partala & Surakka, 2003)		**(A. OCULAR)** PUPIL.	**(PSYCHOSOCIAL)** EMOTIONS.	
C J Harmer et al.		**(A. GLANDULAR)** SEROT.	**(PSYCHOSOCIAL)**	

(C J Harmer et al., 2003)			MOOD, ENERGY, ANXIETY and EMOTIONS*.	
Nwe et al. (Nwe et al., 2001)	**(EXP. ORAL)** SPEECH.			
Buchanan & Lovallo (Buchanan & Lovallo, 2001)		**(A. MUSCULAR)** EMG. **(A. GLANDULAR)** CORT.	**(PSYCHOSOCIAL)** EMOTIONS.	
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)		**(A. CARDÍACA)** PPG(BVP(HR)) and ECG(HR, HRV). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** STRESS.	
Vrijkotte et al. (Vrijkotte et al., 2000)		**(A. CARDÍACA)** BP(SBP, DBP) and ECG(HR, HRV, IBI(RMSSD (VAGAL)).	**(DEMOGRAPH)** AGE. **(PSYCHOSOCIAL)** PERSON, STRESS, and MOOD. **(RECOGNIZED)** ACADDG, PHYSI, WORKYEARS, WEIGHT, HEIGHT, BMI and WAIST. **(INTEGRATION)** CAFFEI, ALCOH, and SMOKING.	**(OTHER)** ACC.
Ritz et al. (Ritz et al., 2000)		**(A. CARDÍACA)** HR, BP(SBP, DBP). **(A. RESPIRATORY)** ROS, RR and VT. **(SKIN)** EDA.	**(PSYCHOSOCIAL)** EMOTIONS.	
L. S. Chen et al. (L. S. Chen et al., 1998)	**(FACIAL EXP.)** EYES, EYEBROWS, MOUTH, WRINKLES, and FROWN. **(EXP. ORAL)** SPEECH and PITCH.			
J. Healey & Picard (J. Healey & Picard, 1998)		**(A. CARDÍACA)** PPG(BVP(HR)). **(A. RESPIRATORY)** RESP. **(SKIN)** EDA. **(A. MUSCULAR)** EMG.		
Rajita Sinha (Rajita Sinha, 1996)		**(A. CARDÍACA)** ECG(HR) and BP(SBP, DBP). **(SKIN)** EDA and ST. **(A. MUSCULAR)**	**(PSYCHOSOCIAL)** EMOTIONS.	

		EMG. **(A. OCULAR)** EOG.		
Scott R. Vrana (Scott R. Vrana, 1993)		**(A. CARDÍACA)** ECG(HR). **(SKIN)** EDA. **(A. MUSCULAR)** EMG.	**(PSYCHOSOCIAL)** EMOTIONS.	
R Sinha et al. (R Sinha et al., 1992)		**(A. CARDÍACA)** ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP) and PCG.	**(PSYCHOSOCIAL)** EMOTIONS.	

() represents a raw signal

3. COLLECTION INSTRUMENTS & SENSORS

Emotional recognition is an interdisciplinary research area involving several fields of knowledge: computer science, cognitive science, and psychology (Aracena et al., 2016). The ability of systems to recognize people's emotions and tailor their actions according to that recognition, is an area of Human-Computer Interaction (HCI) research (Gunes & Piccardi, 2007) (Jerritta et al., 2011). Endowing computers and robots with the ability to understand emotions is an area of study of Affective Computing (AC) (Gogia et al., 2016) (Zhai & Barreto, 2006), and will be an important step in facilitating the interaction between devices and people (Jerritta et al., 2011) (Alabdulkarim, 2015) (Rani & Sarkar, 2006).

In light of the inability to measure emotions directly (Nawasalkar et al., 2013), researchers resort to instruments and sensors to collect context data to be correlated by emotion detection systems (Sano & Eng, 2016). Despite the objective nature of the data collected by the devices, their emotional meaning is not direct, with only their bidirectional influence on emotions known (i.e. emotions are influenced and can influence context signals) (Rani & Sarkar, 2006). Questionnaires, on the other hand, allow the collection of direct information of what is intended to be assessed (e.g. emotions), but the subjective content of the answers given by people can lead to inaccurate measurements (Caballe, 2015) (Sano & Eng, 2016) (Johnston, Propper, & Shields, 2009). In this context, researchers choose to collect data of both types (cf. objective and subjective measurement), with the aim of correlating them and extracting automatic deduction of emotions from them (Rani & Sarkar, 2006) (Nawasalkar et al., 2013) (Gogia et al., 2016).

Objective measurement instruments, despite collecting accurate data, require investment and the use of sensors that may be obstructive or intrusive (Guinot Jimeno, Yuste Bielsa, Cuadros Fernández, Lorente Rodríguez, & Mercadé Bellido, 2011). The subjective measurement obtained by questionnaires and interviews, on the other hand, facilitate generalization to some extent (e.g. the Product Emotion Measurement Instrument (PrEmo) allows respondents not to have to verbalize the emotions felt (Wassink, 2013)) and are the most widely used techniques for emotional assessment (Fulton & Medlock, 2003) (Mandryk & Atkins, 2007). In this context, we decided to summarize the instruments and sensors of the investigations under study, grouping them by the type of measurement they perform, i.e. objective or subjective.

In order to facilitate the reading of the data, we decided to identify the instruments used by the authors between curly brackets (i.e. {}) indicating it is an instrument and the sign collected within curly brackets (i.e. ()) symbolizing data collected from the context (i.e. raw).

The following table summarizes the various instruments used by the researchers considered in this literature survey.

DESCRIPTION	ID	OBJECTIVE	TYPE
OBJECTIVE MEASUREMENT			
Grass 78B	**78B**	A device used in the measurement of physiological signals.	T. obstructive
A655sc Infrared Camera	**A655SC**	Camera for high resolution thermal imaging.	Non-obstructive T.
Biosemi Active II	**ACTIVEII**	Device for collecting signals from electrodes.	T. obstructive

Affectiva Q	**AFFECTIVAQ**	Enable wireless EDA, ST, and ACC collection.	Slightly obstructive T.
App	**APP**	Application referenced and not fully identified by the author.	Non-obstructive T.
Applied Science Laboratories 4000	**ASL4000**	PUPIL monitoring device.	T. obstructive
Applied Science Laboratories 504	**ASL504**	Camera and infrared source for eye-tracking.	T. obstructive
Audio	**AUDIO**	Pre-recorded or captured audio sequences in real time.	Non-obstructive T.
BeWell	**BEWELL**	Application that promotes the user's personal health and well-being.	Non-obstructive T.
Zephyr BioHarness	**BIOHARNESS**	Wireless device for ECG and RESP collection.	Slightly obstructive T.
Brainquiry PET	**BQPET**	Device for collecting the EEG.	Slightly obstructive T.
High Fidelity 3D Facial Image Capture	**DI3D**	Image capture system.	Non-obstructive T.
EyeLink 1000	**EL1000**	Eye tracker used in PUPIL data collection.	T. obstructive
Emotion-Board	**EMOTIONBOARD**	Device for measuring the EDA on the fingers.	Slightly obstructive T.
EmotionSense	**EMOTIONSENSE**	Application used in social psychology studies for emotional detection.	Non-obstructive T.
Emotiv Epoc	**EPOC**	EEG collection device.	T. obstructive
EQ-Radio	**EQ-RADIO**	Emotional recognition system based on WiFi signal.	Non-obstructive T.
Existing data	**EXISTINGDATA**	Data obtained from other information sources (e.g. other systems).	Non-obstructive T.
FaceReader	**FACEREADER**	Emotion detection system for images or videos.	Non-obstructive T.
Cambridge Face Tracker	**FACETRACKER**	Face recognition system.	Non-obstructive T.
ADInstruments FE-116 GSR	**FE116**	Device used in the collection of EDA.	T. obstructive
Hans Rudolph flow head 3803	**FH3803**	Device used in the measurement of VT and RR.	T. obstructive
TNO Biomedical Instrumentation IV	**FINAPRESS4**	Instrument used to collect cardiac activity data.	T. obstructive
Infiniti FlexComp	**FLEXCOMP**	Acquisition and monitoring system for physiological context signals.	T. obstructive
Funf	**FUNF**	Application for collecting context data from the smartphone user.	Non-obstructive T.
GM Instruments CS5	**GMCS5**	Device used in the measurement of VT and RR.	T. obstructive
Koralewski Health Lab	**HEALTHLAB**	System for collecting physiological context data.	T. obstructive
Herbon (Herbon et al., 2005)	**HERBON**	Device created by the author for PUPIL data collection.	Slightly obstructive T.
I-cortisol	**I-CORTISOL**	Device used in the CORT measurement process.	T. obstructive

Jawbone	**JAWBONE**	Wristband for collecting activity, sleep patterns, heart activity, etc.	Slightly obstructive T.
Kinect Sensor	**KINECT**	Motion sensor designed for gestural interaction.	Non-obstructive T.
Kusserow (Kusserow et al., 2013)	**KUSSEROW2**	System to monitor the performance of cellists.	Slightly obstructive T.
Kusserow (Kusserow et al., 2013)	**KUSSEROW3**	System to monitor the performance of athletes (ski jumping).	Slightly obstructive T.
Kusserow (Kusserow et al., 2013)	**KUSSEROW4**	System for monitoring stress in daily tasks.	Slightly obstructive T.
Manual	**MANUAL**	Manual (habitual) activity without the use of a device.	T. obstructive
Neurosky MindWave	**MINDWAVE**	EEG signal collection device.	Slightly obstructive T.
ADInstruments ML-135	**ML135**	Device used in the collection of physiological data.	T. obstructive
ADInstruments ML-309	**ML309**	Device used in the collection of temperature.	T. obstructive
ADInstruments ML870 PowerLab 8/30	**ML870**	Device used in the collection of physiological data.	T. obstructive
g.MOBIlab+	**MOBILAB**	Portable physiological signal acquisition system (e.g. EEEG, EMG, EOG, etc.)	T. obstructive
Grass Model15	**MODEL15**	Device used in context data collection (e.g. CORT).	T. obstructive
MoodScope	**MOODSCOPE**	Application for inferring the user's mood.	Non-obstructive T.
Motion Logger	**MOTIONLOGGER**	Device used for sleep estimation and environmental data collection.	Slightly obstructive T.
BioPac MP100	**MP100**	Device used in the collection of physiological data.	T. obstructive
BioPac MP150	**MP150**	Device used in the collection of physiological data.	T. obstructive
Murali (Murali et al., 2015)	**MURALI**	System for physiological data collection (e.g. ECG, ICG, etc.)	T. obstructive
BioPac NIBP100D	**NIBP100D**	Non-invasive BP monitoring system.	T. obstructive
Pictures	**PICTURES**	Sequence of pre-recorded or captured images in real time.	Non-obstructive T.
Procomp Infiniti	**PROCOMP**	Device for collecting various physiological signals (e.g. EMG, EDA, ECG, and RESP).	T. obstructive
Raudonis (Raudonis, 2013)	**RAUDONIS**	Device created by the author to track the gaze.	Slightly obstructive T.
Coulbourn S71-22	**S71-22**	Device used to collect physiological data.	T. obstructive
Coulbourn S75-01 Hi Gain Bioamplifier	**S75-01**	Device used to collect physiological data.	T. obstructive
Spacelabs 90207	**S90207**	Allows ambulatory BP measurement	T. obstructive
Sarstedt Salivette	**SALIVETTE**	Device used for saliva collection.	T. obstructive
Shore	**SHORE**	System for real-time emotional detection.	Non-obstructive T.
Toshiba Silmee Bar Type	**SILMEEBTYPE**	Device for ECG, PPG and BP collection	Slightly obstructive T.
Tohisba Silmee W20/W21	**SILMEEW2X**	Wristband used for physical activity tracking (collects ST and HR).	Slightly obstructive T.

Siemens Siregnost FD 5	**SIREGNOSTFD5**	Device used in the measurement of ROS.	T. obstructive
Talk Assistant	**TALKASSIST**	System designed to monitor the speaker's performance during the speech.	Slightly obstructive T.
GSR T-Sens	**TGSR**	Device for collecting EDA through the fingers.	T. obstructive
Tobii Pro TX300	**TX300**	System used to collect information related to PUPIL.	Non-obstructive T.
Undefined<tag> (undefined<tag>)	**UNDEFINED<TAG>**	Non-referenced device for collecting the signal indicated in <TAG>.	T. obstructive
Video	**VIDEO**	Pre-recorded or captured video sequences in real time.	Non-obstructive T.
VU-MAS	**VU-MAS**	System for acquisition of physiological context signals (e.g. HR).	T. obstructive
Sony XC-EI30	**XCEI30**	Professional video camera for image collection.	Non-obstructive T.
Zhang (J. Zhang et al., 2013)	**ZHANG**	Author's specific system for collecting EOG through electrodes.	Slightly obstructive T.
SUBJECTIVE MEASUREMENT			
Affect Grid	**AFFECTGRID**	Nonverbal questionnaire based on CIRCUMPLEX for collecting EMOTIONS.	Formal Questionnaires
Affect Intensity Measure	**AIM**	Questionnaire used to evaluate EMOTIONS in life events.	Formal Questionnaires
Beck Depression Inventory	**BDI**	Questionnaire used to assess DEPRESSION.	Formal Questionnaires
Beck Depression Inventory	**BDI**	Questionnaire to assess DEPRESSION.	Formal Questionnaires
Big Five Inventory Personality Test	**BFIPT**	Questionnaire to evaluate PERSON.	Formal Questionnaires
Befindlichkeits Scale (Zerssen Mood Scale)	**BFS**	Questionnaire to measure MOOD.	Formal Questionnaires
Circumplex Model of Affect	**CIRCUMPLEX**	Nonverbal questionnaire used to represent emotions (adapted by LikamWa et al. (LiKamWa et al., 2013) for collecting EMOTIONS).	Formal Questionnaires
Differential Emotion Scale	**DES**	Questionnaire used to measure EMOTIONS.	Formal Questionnaires
Effort-Reward Imbalance	**ERI**	Questionnaire used to measure work-related STRESS.	Formal Questionnaires
Social Support Satisfaction Scale	**ESSS**	Questionnaire to evaluate the social support received.	Formal Questionnaires

Goldberg Anxiety and Depression Scale	**GADS**	Questionnaire for assessing DEPRESSION and ANXIETY.	Formal Questionnair es
HealthyOffice	**HEALTHYOFFICE**	MOOD's self-reporting smartphone app.	Formal Questionnair es
Informal questionnaire	**INFORMAL**	Questionnaire with unverified validity.	Informal questionnaire s
Long-term Difficulties Inventory	**LDI**	Questionnaire for evaluating the daily DIFFICULTIES.	Formal Questionnair es
List of Threatening Experiences	**LTE**	Questionnaire to assess exposure to threats and life-changing events (LIFEEVENTS)	Formal Questionnair es
Myers Briggs Type Indicator	**MBTI**	Questionnaire for categorizing PERSON.	Formal Questionnair es
Marlowe-Crowne Social Desirability Scale	**MCSDS**	Questionnaire used to measure social desirability	Formal Questionnair es
Minnesota Multiphasic Personality Inventory	**MMPI**	Questionnaire used to evaluate PERSON.	Formal Questionnair es
Oxford Happiness Questionnaire	**OHQ**	Questionnaire to measure HAPPY.	Formal Questionnair es
Positive And Negative Affect Schedule	**PANAS**	Questionnaire to measure EMOTIONS.	Formal Questionnair es
Positive And Negative Affect Schedule - Exapanded Form	**PANAS-X**	Expanded version of the PANAS questionnaire.	Formal Questionnair es
Patient Health Questionnaire	**PHQ-9**	Questionnaire for DEPRESSION assessment.	Formal Questionnair es
Profile Of Mood States	**POMS**	Questionnaire to assess MOOD.	Formal Questionnair es
Emotion Measurement Instrument	**PREMO**	Nonverbal questionnaire to assess EMOTIONS.	Formal Questionnair es
Psychosomatic Symptom Checklist	**PSC**	Questionnaire used to measure HEALTH.	Formal Questionnair es
Pittsburgh Sleep Quality Index	**PSQI**	Questionnaire to measure the quality and standards of SLEEP.	Formal Questionnair es
Perceived Stress Scale	**PSS**	Questionnaire used to measure STRESS.	Formal Questionnair es

Questionnaire for Mental Imagery	**QMI**	Questionnaire to assess the ability to interpret images.	Formal Questionnaires
Rosenberg Self-Esteem Scale	**RSES**	Questionnaire used in the evaluation of self-esteem.	Formal Questionnaires
Self-Assessment Manikin	**SAM**	Nonverbal questionnaire for measuring EMOTIONS.	Formal Questionnaires
Self-assessment Morningness-Eveningness	**SAME**	Questionnaire to collect information about circadian cycles (e.g. SLEEP).	Formal Questionnaires
Zung Self-rating Depression Scale	**SDS**	Questionnaire to assess DEPRESSION.	Formal Questionnaires
Short-Form 12	**SF-12**	Questionnaire to measure HEALTH-related quality of life.	Formal Questionnaires
Social Radjustment Rating Scale	**SRRS**	Questionnaire for measuring stressful life events.	Formal Questionnaires
State-Trait Anxiety Inventory	**STAI**	Questionnaire used in the measurement of ANXIETY.	Formal Questionnaires
Spielberger State-Trait Anger Scale	**STAS**	Scale used to measure ANGER.	Formal Questionnaires
Toronto Alexithymia Scale	**TAS**	Questionnaire to assess the ability to interpret emotions.	Formal Questionnaires
OTHER INSTRUMENTS			
Biopac AcqKnowledge	**ACQK**	Application for processing information from collection instruments.	Other Instruments
BioExplorer	**BIOEXPLORER**	Application for neurofeedback and biofeedback.	Other Instruments
BioGraph Infinity	**BIOGRAPH**	Application used to support data recording and analysis in graphical form.	Other Instruments
Captiv	**CAPTIV**	Application that facilitates the process of recording data.	Other Instruments
Hitachi MS-DS400	**DS400**	Used to support video recording.	Other Instruments
Emotion Avatar Images	**EAI**	Used to simulate behavior through avatar images.	Other Instruments
Epoc SDK	**EPOC-SDK**	SDK to enable integration with the EPOC-SDK.	Other Instruments
Human Activity Recognition	**HAR**	Algorithm for human activity recognition (e.g. walking, sitting, etc.)	Other Instruments
Matlab HRVAS	**HRVAS**	MATLAB AddOn for HRV extraction.	Other Instruments

Interview	**INTERVIEW**	Technique used for data collection and screening.	Other Instruments
Kinect SDK	**KINECT-SDK**	SDK to enable integration with KINECT.	Other Instruments
ADInstruments LabChart	**LABCHART**	Application used to support data acquisition and pre-processing.	Other Instruments
Grass Link15	**LINK15**	Application that supports the MODEL15 data recording process.	Other Instruments
Mindwave SDK	**MINDWAVE-SDK**	SDK to enable integration with MINDWAVE.	Other Instruments
Observation	**OBSERVATION**	Technique used for data collection.	Other Instruments
PsyScope	**PSYSCOPE**	Tool used in experimental control.	Other Instruments
Tobii Studio	**TSTUDIO**	Application used in investigations with signs related to the ocular context.	Other Instruments

3.1. OBJECTIVE MEASUREMENT

The data obtained by the devices tends to represent objective context data points (Rani & Sarkar, 2006) (e.g. the HR value, ST, or CALL number objectively represent measurements of cardiac context, skin, and social interaction). Although it is not possible to map these data directly onto emotions, they can provide important information for inferring people's cognitive and emotional state (Schumm et al., 2010).

The need to collect context data means installing collection means (e.g. devices and sensors) that may obstruct the user's daily habits. However, for unbiased and accurate collection of context data to be possible, people have to be unaware of the presence of these instruments (Ouwerkerk, Pasveer, & Langereis, 2008) (Alabdulkarim, 2015). In this context the obstructivity of the devices assumes an important role to take into account when deciding which ones to use because, if they influence the natural environment of the user, they may also be decreasing quality of the collected data subtracting impartiality from them (Ouwerkerk et al., 2008). Intrusiveness is also an important consideration when collecting private data. Inspecting the context means accessing sensitive and private information of the users and there are security and ethical issues to be ensured. Notwithstanding the importance of intrusiveness, it is on the obstructiveness of the devices that we intend to focus the study in this section because of the need to ensure the quality of the data collected, reducing the possibility of contamination. In this context, we will use the term obstructivity to represent the possible blockage of people's normal activities caused by the use of collection instruments.

Obstructive approaches alter users' habits, use cumbersome devices and sensors, or require manual data entry disrupting people's normal activities (Z. Chen et al., 2013). But obstructiveness should also be analyzed in another perspective: the lower the degree of obstructiveness, the easier it is for people to be predisposed to accept the collection of data from their context (Schumm et al., 2010). Thus, given the importance of obstructiveness in the data collection process, we decided to classify the different objective measurement devices and sensors present in the analyzed investigations according to this characteristic: non-obstructive techniques; low obstructive techniques; and obstructive techniques.

This categorization is based on our subjective assessment of the obstruction caused by each reported device, and intends to support the selection process of instruments and sensors to be used during the experimental phase of our research. We intend to select instruments whose use goes as unnoticed as possible by the user, not obstructing their normal activity, and thus decrease the risk of interference in the collected values, giving them quality.

3.1.1. Non-obstructive techniques

This section deals with techniques that do not imply obstructivity for users, or that present such a low degree that it can be considered negligible (e.g. slight performance drop caused by the installation of a new application on the smartphone or computer). Also included in this section are devices that, despite having been used in research in controlled environments and therefore presenting some obstructivity in the experimental phase, their actual implementation may represent a zero or very residual level of obstructivity (e.g. video cameras). Finally, we also include context data from existing databases typically managed and fed by public organizations or state bodies (e.g. *Instituto Português do Mar e da Atmosfera* (IPMA)).

To collect data, devices and sensors are needed. The only way to achieve this without influencing people's environment is by using or enhancing devices or sensors that are already part of their everyday lives. Thus, it is unavoidable to analyze the use of smartphones as a means to collect context data. **Smartphones** are pervasive platforms for opportunistic sensing of behaviors and opinions (Madan et al., 2012). As they currently occupy a fixed place in the lives of human beings (Eckert et al., 2016) (N. D. Lane et al., 2010) and are used by millions of people, smartphones are the most suitable tool to support non-obtrusive data collection in social or psychophysiological research (Rachuri et al., 2010). Smartphones can be viewed as programmable platforms for monitoring and tracking people's well-being (N. D. Lane et al., 2010). Real-time inference of behaviors is already possible today allowing, for example, users to receive feedback about their lifestyle or health-related choices (N. Lane et al., 2011). Although they are already distributed with several embedded sensors (e.g. accelerometer, gyroscope, GPS, camera, microphone, etc.) it is expected that the technological evolution will promote the increase in the number of sensors that integrate smartphones, iteratively widening in time the range of possible applications (N. Lane et al., 2011) (N. D. Lane et al., 2010). Thus, it is expected that the number of applications related to monitoring and evaluating the physical, social and mental well-being of users will increase (N. Lane et al., 2011).

There are several context variables possible to extract from the smartphone (e.g. CALL, SMS, contact list, location, proximity, humidity, etc.) (Jaques et al., 2015) (Bogomolov et al., 2014) (Sano & Eng, 2016) (Sano & Picard, 2013b) allowing for an analysis of social interactions on an ongoing basis, and achieving greater accuracy than traditional methods in social assessment (e.g. questionnaires, interviews, and observation) (Madan et al., 2012). Based on smartphone logs, researchers are able to create new information related to users' lives: Bogomolov et al., studied ways to automatically recognize people's happiness (Bogomolov, Lepri, & Pianesi, 2013); Moturu et al. studied the relationship between sleep, mood, and social interaction data (Moturu et al., 2011); Dong et al. created a model to define the structure of social interactions in a student dormitory (Dong et al., 2011); Li et al., created a system for recognizing loneliness (Li, Shi, Wang, & Liu, 2016); Sano et al., Bogomolov et al. and Bauer et al., studied stress and ways to predict it (Sano & Picard, 2013b) (Bogomolov et al., 2014) (Bauer & Lukowicz, 2012); Chet et al. used the smartphone to monitor sleep in a non-obstructive way (Z. Chen et al., 2013); etc.

There are several smartphone applications used by researchers to collect and process context data: MoodScope **{MOODSCOPE}** infers user mood based on smartphone usage data (cf. SMS, EMAIL, CALL, APPS, BROWSER and LOCAL) (LiKamWa et al., 2013); EmotionSense **{EMOTIONSENSE}** is a platform for social psychology studies that has the ability to detect user activities and emotions, and verbal and proximity interactions between elements of social groups (Rachuri et al., 2010); funf **{FUNF}** is a sensing platform used for collecting social context data from the smartphone (e.g. CALL, SMS, etc.) (Aharony & Gardner, 2011); and BeWell **{BEWELL}** is an application that promotes personal health by assisting the user in managing their well-being through monitoring physical activity, social interaction, and sleep patterns (N. Lane et al., 2011). In addition to these, there are other applications referenced in the research that are not fully identified by the authors **{APP}** (e.g. (Muaremi et al., 2012), (Eckert et al., 2016), etc.) or that are modified from existing ones (e.g. Sano et al. modified FUNF in their investigation (Sano & Eng, 2016)).

Another way to collect data in a non-obtrusive way will be through the use of sensors already existing in the natural environment of users (e.g. cameras, microphones, WiFi signal, etc.). This group includes devices that allow passive collection of **video**, **audio,** and **image, and** do not imply any action or behavioral change by the user. The literature reports several experiments using instruments related to video **{VIDEO}**, audio **{AUDIO}** or image **{PICTURES}** that, while signifying the natural obstructivity of a laboratory experiment, can signify low or no obstructivity in real-world implementations (e.g. (S. H. Lee et al., 2016)). Included in these groups are resources that are pre-collected (e.g. video sequences, audio snippets or photographs) or collected at the time of processing (cf. cameras, microphones or cameras). The VIDEO category includes frame-by-frame video processing (e.g. (Singh et al., 2015), (Agrawal et al., 2013)) and any type of video: with or without audio, 2D, 3D, 4D, thermal (e.g. (Z. Zhang et al., 2016) etc.). The AUDIO category includes: conversations, talks (voice), speeches or uttered utterances (e.g. (Korkmaz & Atasoy, 2015)).

Among the instruments present in the literature, we listed the ones used in the researches we analyzed: the Cambridge Face Tracker **{FACETRACKER}** is a system for face recognition through neural networks from video properties (Thomas, Baltru?aitis, Robinson, & Vivian, 2016); the High Fidelity 3D Facial Image Capture **{DI3D}** is a passive high resolution 3D image capture system, possible to use with any type of digital cameras (Dimensional Imaging LTD, 2017); FLIR's A655sc **{A655SC}** infrared camera enables the collection of high resolution (cf. 640x480) thermal images at temperatures in the range [-40;150]ºC (FLIR Systems, n.d.); the Kinect Sensor **{KINECT}** is a motion sensor designed to interact with Microsoft Xbox 360 players through gestures and verbal commands (there is also a Windows version) (Leyvand et al., 2011) (Vermun et al., 2013); Noldus' FaceReader **{FACEREADER}** is an emotional detection system based on facial recognition in offline or livestream images or videos (Noldus, 2017) (Matlovic et al., 2016); Shore **{SHORE}** is Fraunhofer's system that also does emotional detection through facial recognition, and allows real-time facial detection and analysis (Fraunhofer IIS, 2017); the EQ-Radio **{EQ-RADIO}** created by Zhao et al., is a system for emotional recognition based on the WiFi signal, capable of detecting heartbeats from the reflection of the RF signal with an accuracy similar to that of the body ECG (Zhao et al., 2016); the Sony XC-EI30 **{XCEI30}** is a professional video camera widely used in image processing (Sony Inc., 2010); the Tobii Pro TX300 **{TX300}** is a highly accurate system that collects data about gaze even with considerable head movements, it allows to detect and collect data about PUPIL, eye movement, etc. (Tobii AB, 2015);

Some research also uses existing data **{EXISTINGDATA}** (e.g. public databases: the *Instituto Português do Mar e da Atmosfera* (IPMA) can provide environmental context data; the *Instituto Nacional de Estatística* (INE) and the PORDATA service can provide economic and demographic data, etc.). There are investigations that use data available in other systems: Bogomolov et al. used Wolfram Alpha (Wolfram Alpha, 2013) to obtain daily data about WEATHER (e.g. ambient temperature, pressure, precipitation, humidity, visibility, wind, etc.) (Bogomolov et al., 2014); Hernandez et al. used call records from a call center to study employees (Hernandez et al., 2011), etc.

RESEARCH	INSTRUMENTS & SENSORS	
	NON-OBSTRUCTIVE TECHNIQUES	OTHER
S. H. Lee et al. (S. H. Lee et al., 2016)	{VIDEO} *(FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, NOSE, LIPS, CHEEKS, JAW, MOUTH)*.	
Eckert et al. (Eckert et al., 2016)	{APP, PICTURES} *(FACS, CAUL, EYES, EYEBROWS, NOSE, MOUTH*).	
Matlovic et al. (Matlovic et al., 2016)	{FACEREADER, SHORE}.	**T. obstructive:** {EPOC} *(EEG)* and {TGSR} *(EDA)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {TSTUDIO, CAPTIV}.
Gogia et al. (Gogia et al., 2016)	{KINECT, VIDEO} *(HEAD)*.	**Lightly obstructive T:** {MINDWAVE} *(EEG)*. **(OTHERS)** {MINDWAVE-SDK, KINECT-SDK}.
Z. Zhang et al. (Z. Zhang et al., 2016)	{DI3D, A655SC, VIDEO} *(HEAD, FACS, ST)*.	**T. obstructive:** {MP150, NIBP100D} *(BP(SBP, DBP), HR, PR, RESP(RR)) and* {Undefined(EDA)} *(EDA)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Sano & Eng (Sano & Eng, 2016)	{FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*.	**Lightly obstructive T:** {AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*. **T. obstructive:** {Undefined(EEG)} *(EEG)*, {Undefined(*PSG*)} *(PSG)*, {Undefined(EOG)} *(EOG)*, {Undefined(*EMG*)} *(EMG)* and {Undefined(MELAT)} *(MELAT)*. **(Q. FORMAIS)** {SAME, PSQI} *(SLEEP)*, {MBTI, BFIPT} *(PERSON)*, PSS} *(STRESS)*, {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*. **(Q. INFORMAL)** {INFORMAL} *(AGE, GENDER, FTF, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*.
Zhao et al. (Zhao et al., 2016)	{EQ-RADIO} *(HR(IBI(RMSSD, SDNN)), RESP) and* {VIDEO**}.	**T. obstructive:** {Undefined(ECG)} *(ECG(HR))*.

	*** used to compare the results obtained with *Microsoft's Cognitive Services* (Microsoft, 2017b).	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Adams & Robinson (Adams & Robinson, 2015)	{FACETRACKER} *(FACS (HEAD, EYELIDS, EYEBROWS, CHEEKS, EYES, NOSE, WRINKLES, LIPS, CHIN, JAW), GAZE)*.	
Turan et al. (Turan et al., 2015)	{PICTURES, VIDEO} *(FACE, EYES).*	
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	{AUDIO} *(SPEECH, VOLUME)*.	
Lalitha et al. (Lalitha et al., 2015)	{AUDIO} *(SPEECH, PITCH and VOLUME)*.	
Singh et al. (Singh et al., 2015)	{VIDEO} *(SHOULDERS, HANDS)*.	
Jaques et al. (Jaques et al., 2015)	{APP} *(CALL, SMS, SCREEN, LOCAL)*.	**Lightly obstructive T:** {AFFECTIVAQ} *(EDA, ST, ACC).* **(Q. INFORMAL)** {INFORMAL} *(HAPPY, ACADCL, ACADEX, ACADST, PHYSI, SOCIAL, CAFFEI, ALCOH, DRUGS, STRESS, HEALTH, ENERGY, ALERT, CALM, SLEEP, NAP)*.
Saha et al. (Saha et al., 2014)	{KINECT} *(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN, ACC).*	**(OTHERS)** {KINECT-SDK}.
Bogomolov et al. (Bogomolov et al., 2014)	{APP} *(CALL, SMS, PROXIMITY)* and {EXISTINGDATA} *(WEATHER)*.	**(Q. FORMAIS)** {BFIPT} *(PERSON)*. **(Q. INFORMAL)** {INFORMAL} *(STRESS)*.
Agrawal et al. (Agrawal et al., 2013)	{VIDEO} *(EYES, MOUTH, LIPS, SKIN)*.	
Soleymani et al. (Soleymani et al., 2013)	{VIDEO} *(HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH)*.	**T. obstructive:** {ACTIVEII} *(EEG)*. **(OTHERS)** {OBSERVATION} *(EMOTIONS)*.
Vermun et al. (Vermun et al., 2013)	{KINECT} *(HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP, KNEES)*.	
Kawai et al. (Kawai et al., 2013)	{XCEI30} *(PUPIL)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {DS400}.
Babiker et al. (Babiker et al., 2013)	{TX300} *(EYES, GAZE, PUPIL)*.	**(Q. FORMAIS)** {PANES-X} *(EMOTIONS).*
LikamWa et al. (LiKamWa et al., 2013)	{MOODSCOPE} *(SMS, EMAIL, CALL, APPS, BROWSER, LOCAL)*.	**(Q. FORMAIS)** {CIRCUMPLEX} *(MOOD)*.

Bauer & Lukowicz (Bauer & Lukowicz, 2012)	{APP} *(LOCAL, PROXIMITY, CALL, SMS)*.	
Yang & Bhanu (S. Yang & Bhanu, 2011)	{VIDEO} *(HEAD, FACE)*.	**(OTHERS)** {EAI}.
Dhall et al. (Dhall et al., 2011)	{PICTURES, VIDEO} *(FACE)*.	
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	{VIDEO} *(PUPIL)*.	**T. obstructive:** {ML870} *(ECG(HRV), PPG)*.
Hernandez et al. (Hernandez et al., 2011)	{EXISTINGDATA} *(CALL)*.	**Lightly obstructive T:** {AFFECTIVAQ} *(EDA)*. **(Q. INFORMAL)** {INFORMAL} *(STRESS)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
N. Lane et al. (N. Lane et al., 2011)	{BEWELL} *(SLEEP, PHYSI, TALK, LOCAL, ACC)*.	**(Q. INFORMAL)** {INFORMAL} *(DEPRESSION, SLEEP, WELLBEING)*. **(OTHERS)** {HAR}.
H. Wang et al. (H. Wang et al., 2010)	{VIDEO} *(EYES)*.	
Gunes & Piccardi (Gunes & Piccardi, 2007)	{VIDEO} *(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, CHEEKS, FOREHEAD, JAW, NOSE, HANDS, FINGERS, FISTS, PALMS, SHOULDERS, NECK).*	
Castellano et al. (Castellano et al., 2007)	{VIDEO} *(ARMS)*.	
Mandryk & Atkins (Mandryk & Atkins, 2007)	{VIDEO, AUDIO}***. *** only collected.	**T. obstructive:** {PROCOMP} *(EDA, ECG(HR), EMG)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {BIOGRAPH}.
Sebe et al. (Sebe et al., 2006)	{VIDEO} *(HEAD, EYEBROWS, EYELIDS, MOUTH)* and {AUDIO} *(VOLUME, SPEECH, PITCH)*.	
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	{VIDEO***}. *** used in conjunction with OBSERVATION for teasing.	**T. obstructive:** {FLEXCOMP} *(ECG(HR, HRV), EMG, EDA, RESP).* **(Q. INFORMAL)** {INFORMAL} *(STRESS)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
Busso et al. (Busso et al., 2004)	{VIDEO} *(FOREHEAD, EYEBROWS, EYES, CHEEKS) and* {AUDIO} *(PITCH, VOLUME)*.	

Nwe et al. (Nwe et al., 2001)	{AUDIO} *(SPEECH)*.	
L. S. Chen et al. (L. S. Chen et al., 1998)	{AUDIO} *(SPEECH, PITCH)* and {VIDEO} *(EYES, EYEBROWS, MOUTH, WRINKLES, FROWN)*.	

() represents a raw signal; and {} an instrument.

3.1.2. Low Obstruction Techniques

The authors believe that the degree of obstructiveness is not the same for all devices and sensors that influence the normal activity of people. For example, a belt to measure chest cavity expansion will be less obstructive than the use of masks to determine the amount of gas exchanged through the lungs (Jennifer a Healey et al., 2000). Although both measure breathing, the first option does not prevent the user from continuing to perform normal tasks, i.e. it is not totally obstructive. There are also other devices that, although they have only been used in experimental settings, appear to be close to a real-life implementable version. For example J. Zhang presents some glasses for collecting the EOG and transmitting it via Wireless Fidelity (WiFi). With some miniaturization (e.g. WiFi transmitter), the device could be used by people very close to normal glasses.

The existence of sensors with some obstructivity but whose use may be forgotten during collection motivated us to create the group of low obstructive devices. Thus, this section presents techniques whose measurement becomes transparent with use (i.e. technology that disappears into the background), promoting the quality and integrity of the context data collected (Weiser, 1991) (Weiser & Brown, 1996).

In the research reviewed there were several instruments classified as low obstructive: J. Zhang et al. created an inexpensive and easy-to-use wearable system **{ZHANG}**, capable of collecting EOG using electrodes and transmitting the collected data to a computer via WiFi (J. Zhang et al., 2013); Raudonis mounted on an eye armor **{RAUDONIS1}**, a gaze tracking device composed of an infrared (IR) light emitter and a small video camera (Raudonis, 2013); similarly, Herbon et al. mounted on a helmet a camera for image collection of the PUPIL **{HERBON}** (Herbon et al., 2005); the Zephyr BioHarness **{BIOHARNESS}** is a wireless device that allows the collection of ECG signal and RESP-related data (Zephyr Technology, 2012); the Neurosky MindWave **{MINDWAVE}** also measures EEG but is a lightweight, self-powered headset with wireless communication (Neurosky, 2017); Affectiva's Q pulse sensor **{AFFECTIVAQ}** (converted to a product) communicates wirelessly, and allows collection of EDA and ST (also includes ACC) (Affectiva Inc., 2014) (Affectiva Inc., 2013); The Emotion-Board **{EMOTIONBOARD}** measures EDA in the fingers using small straps (the small integrated ACCs allow measuring information about finger and hand movement as well) (Schumm et al., 2008); AMI's Motion Logger **{MOTIONLOGGER}** is an actigraph that allows sleep estimation while collecting environmental context data (Ambulatory Monitoring, n.d.) (Mill, Road, Ardsley, & York, n.d.); the Tohisba Silmee W20/W21 wristband **{SILMEEW2X}** tracks physical activity (e.g. number of steps, distances walked, etc.) and can also measure ST, HR, sleep quality, etc. (the W21 model also has GPS) (Toshiba, 2015) (Linder, 2015); the Silmee Bar Type **{SILMEEBTYPE}** also from Toshiba is a small device to put on the chest, capable of collecting ECG, PPG, BP (via PWTT), etc. (Silmee, n.d.) (Fuke, 2013); the Talk Assistant **{TALKASSIST}** created by Kusserow et al. was developed in order to monitor and give feedback to public speakers simultaneously with their presentations, it is composed of several sensors (e.g. HR, EDA, ACC, etc.) (Kusserow et al., 2013); the wearable system created by Kusserow **{KUSSEROW2}** to monitor and analyze cellists during performances, is composed of an ECG with chest electrodes and pulse ACC (Kusserow et al., 2013); Kusserow et al. also developed a wearable heart activity analysis system for use by ski jumping athletes **{KUSSEROW3}**, which collects ECG and ACC through miniature sensors placed on the chest (Kusserow et al., 2013); Kusserow's multimodal framework **{KUSSEROW4}**, can estimate stress in various daily activities (cf. onset, duration and intensity) (Kusserow et al., 2013); Brainquiry PET **{BQPET}** is a portable, wireless, low obstructive instrument that collects EEG (currently there are two versions: two and four electrodes), EMG or ECG (Brainquiry, n.d.) (Branquiry, 2017); Jawbone wristbands **{JAWBONE}**, allow the collection of activity, sleep patterns, heart monitoring, etc. (e.g. Lisetti and Nasoz used the BodyMedia SenseWear sensor (currently Jawbone) to collect ADS, HR and ST (Lisetti & Nasoz, 2004)) (Jawbone, 2017); and inertia meter **{IMU}** allows to measure linear and angular motion (used in conjunction with gyroscopes and accelerometers) (xsens, n.d.).

RESEARCH	INSTRUMENTS & SENSORS	
	LOW OBSTRUCTIVE TECHNIQUES	OTHER
Perdiz et al. (Perdiz et al., 2017)	{IMU} *(HEAD)*.	**<u>T. obstructive:</u>** {Undefined(EMG), Undefined(EOG)} *(EMG, EOG)*.
Gogia et al. (Gogia et al., 2016)	{MINDWAVE} *(EEG)*.	**<u>Non-obstructive T:</u>** {KINECT, VIDEO} *(HEAD)*. **(OTHERS)** {MINDWAVE-SDK, KINECT-SDK}.
Sano & Eng (Sano & Eng, 2016)	{AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*.	**<u>Non-obstructive T:</u>** {FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*. **<u>T. obstructive:</u>** {Undefined(EEG)} *(EEG)*, {Undefined(*PSG*)} *(PSG), {Undefined(*EOG)} *(EOG)*, {Undefined(EMG)} *(EMG)* and {Undefined(MELAT)} *(MELAT)*. **(Q. FORMAIS)** {SAME, PSQI} *(SLEEP),* {MBTI, BFIPT} *(PERSON),* PSS} *(STRESS),* {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*. **(Q. INFORMAL)** {INFORMAL} *(AGE, GENDER, FTF, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*.
Zenonos et al. (Zenonos et al., 2016)	{SILMEEW2X, SILMEEBTYPE} *(ECG(HR(IBI(RMSSD, SDNN)), HRV***), PPG(PR, PTT), ST)*. *** obtained through HRVAS.	**(Q. FORMAIS)** {HEALTHYOFFICE} *(MOOD, EMOTIONS)*. **(OTHERS)** {HRVAS} *(HRV)**** and {HAR} *(ACC)*.
Basu et al. (Basu et al., 2016)	{BIOHARNESS} *(ECG, HR, PR, RESP(RR))*.	**<u>T. obstructive:</u>** {ML870, FE116, ML135, ML309} *(EDA, ST)* and {Undefined(EMG)} *(EMG)*. **(OTHERS)** {LABCHART}.
Jaques et al.	{AFFECTIVAQ} *(EDA, ST, ACC)*	**<u>Non-obstructive T:</u>** {APP} *(CALL, SMS, SCREEN, LOCAL)*.

(Jaques et al., 2015)		**(Q. INFORMAL)** {INFORMAL} *(HAPPY, ACADCL, ACADEX, ACADST, PHYSI, SOCIAL, CAFFEI, ALCOH, DRUGS, STRESS, HEALTH, ENERGY, ALERT, CALM, SLEEP, NAP)*.
Kusserow et al. (Kusserow et al., 2013)	{TALKASSIST} *(HR(HRV), EDA, ACC, ST)*, {KUSSEROW2} *(ECG(HR), ACC)*, {KUSSEROW3} *(ECG(HR), ACC)* and {KUSSEROW4} *(HR, ACC)*.	**(Q. INFORMAL)** {INFORMAL} *(STRESS, MOOD)*.
Sano & Picard (Sano & Picard, 2013b)	{AFFECTIVAQ} *(EDA, ACC)* and {FUNF} *(CALL, SMS, LOCAL, SCREEN)*.	**(Q. FORMAIS)** {PSS} *(STRESS)*, {PSQI} *(SLEEP)* and {BFIPT} *(PERSON)*. **(Q. INFORMAL)** {INFORMAL} *(SLEEP, ELECTR, HEALTH, MOOD, ALERT, TIRED, STRESS, NAP, CAFFEI, ALCOH)*.
Raudonis (Raudonis, 2013)	{RAUDONIS1} *(GAZE, EYES, PUPIL)*.	
Hernandez et al. (Hernandez et al., 2011)	{AFFECTIVAQ} *(EDA)*.	<u>**Non-obstructive T:**</u> {EXISTINGDATA} *(CALL)*. **(Q. INFORMAL)** {INFORMAL} *(STRESS)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
Bos (Bos, 2010)	{BQPET} *(EEG)*.	**(OTHERS)** {BIOEXPLORER}.
Setz et al. (Setz et al., 2010)	{EMOTIONBOARD} *(EDA)*.	
Herbon et al. (Herbon et al., 2005)	{HERBON} *(PUPIL)*.	<u>**T. obstructive:**</u> {Undefined(EDA), Undefined(ST), Undefined(HR)} *(EDA, ST, HR)*. **(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(GENDER, AGE, HEALTH, TECHEXPERT)*.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	{JAWBONE} *(EDA, HR, ST)*.	**(Q. INFORMAL)** {INFORMAL} *(AGE, GENDER, ETHNICITY, EMOTIONS)*.

() represents a raw signal; and {} an instrument.

3.1.3. Obstruction techniques

The obstructive techniques section presents the devices and sensors not included in the first two categories (cf. non-obstructive or low obstructive techniques). These are instruments that affect people's lives and whose actual implementation would be difficult. For example, the daily use of electrodes for measuring ECG, EEG or EMG, would be complicated to implement because of the constraint on the performance of people's normal activities. Also considered in this section are techniques whose measurement is done without the use of collection instruments (e. g. administration of medication where the counting is done on the dose) **{MANUAL}**, and instruments that users would be unlikely to lose track of over time even if they used them regularly, i. e., instruments whose use may mean that the impartiality of the data they collect is reduced.

Some investigations do not concretely identify the devices used (i.e. brand, manufacturer, etc.), using only a scientifically recognized generic designation (e.g. ECG, EEG, etc.). Others refer to devices whose antiquity makes it impossible to adopt in current investigations. Still others do not specify the instrument but only the signal collected (e.g. EDA). Thus, it was decided to use the notation {Undefined<tag>}, where tag can take the term used by researchers to identify a signal whose collection device has not been identified (e.g. {Undefined<EMG>} refers to an unspecified instrument for EMG signal collection), or it can take on a generic name used for a collection device when the author does not concretely identify its brand or manufacturer (e.g. {Undefined<ECG>} refers to an ECG whose brand was not mentioned). Several devices are used by researchers in these conditions: the Electrocardiogram **{*Undefined*(ECG)} (**also known as EKG) allows measuring the electrical activity of the heart (Mandryk & Atkins, 2007) (J. Kim & André, 2008) (through it it is possible to extract variables such as HR, HRV, etc. (Jennifer a Healey et al., 2000) (Mandryk & Atkins, 2007); Impedance Cardiography **{*Undefined*(ICG)}** measures the variations in impedance caused by changes in blood volume and velocity in the aorta with each heart beat, and is useful for collecting information about the muscle activity of the heart (Murali et al., 2015); Phtoplethysmography **{*Undefined*(PPG)}** is an optical, non-invasive technique for measuring blood volume changes (venous and arterial) occurring in blood vessels close to the skin (Malik, 2009) (measured at the fingertip shows the blood volume fluctuation at that point reflecting the sympathetic modulation of the finger arterioles) (G. S. H. Chan, Middleton, Lovell, & Celler, 2005); Phonocardiogram **{*Undefined*(PCG)}** is used for analysis of the sounds produced by the heart (e.g. cardiovascular diagnosis, biometric authentication, stress recognition, etc.) (Varghees & Ramachandran, 2016); Electrooculogram **{*Undefined*(EOG)}** is used to collect eye movement by placing electrodes on the eye area (J. Zhang et al., 2013); Electromyogram **{*Undefined*(EMG)}** is used to measure muscle activity at the skin surface by placing sensors on the muscles, or intramuscularly by using needles (Lichtenstein, Antje; Oehme, 2008) (Haag et al., 2004) (Chandler & Cornes, 2012); the instrument to measure electrodermal activity **{*Undefined*(EDA)}**, i.e. the conductive capacity of the skin that increases momentarily upon a person's exposure to an arousing stimulus (e.g. Zhang et al. used a sensor interconnected to a wristwatch (Z. Zhang et al., 2016)) (Jaques et al., 2015); Polysomnography **{*Undefined*(PSG)}** is a technique used to study sleep by monitoring various signals (Armon, 2016).

The research reviewed reports the use of several devices that imply obstructivity for their users: the Procomp Infiniti **{PROCOMP}** is a device from Thought Technology Ltd. composed of several biosensors (cf. EMG, EDA, ECG and RESP) (Infiniti, 2008b) (Infiniti, 2008a); Emotiv's Epoc **{EPOC}** is a low-cost headset consisting of 14 electrodes plus 2 reference (Linh, 2008) (Ramirez, Ramirez, & Vamvakousis, 2015) which should be placed respecting the international 10-20 system (Trans Cranial Technologies Ltd., 2012) (Niedermeyer & Silva, 2005); the Grass 78B **{78B}** Polygraph allows the measurement of physiological signals (e.g. Sinha (Rajita Sinha, 1996)); the Grass Model15 **{MODEL15}** is a digital amplifier created in 1994, it was used to store EMG activity related data (e.g. (Partala et al.)) and, although no longer a distributed product by the current brand owner, was inspiration for current systems (ERIKG Group, 2011) (Natus Medical Inc., 2017); Espoo's Orion Diagnostica **{ORION}** kit (technology currently from Cisbio Bioassays (Rissanen, 2013) (Business Wire, 2007)) allows the measurement of CORT concentrations in saliva using the radioimmunoassay technique (Buchanan et al. used this kit in conjunction with Sarstedt's Salivette **{SALIVETTE}** to facilitate the collection process (Sarstedt, n.d.) (Buchanan & Lovallo, 2001) (Cisbio, 2016)); I-cortisol **{I-CORTISOL}** used by van Eck et al. in conjunction with SALIVETTE, also uses the radioimmunoassay technique (van Eck et al., 2005); various instruments from ADInstruments such as ML870 PowerLab 8/30 **{ML870}** for data collection

(ADInstruments, n.d.-d); FE-116 GSR **{FE116}** for collecting EDA (ADInstruments, n.d.a); ML-309 **{ML309}** for collecting temperature (e.g. ST) (ADInstruments, n.d.c), and the ML-135 **{ML135}** amplifier for physiological signals (ADInstruments, n.d.b); the EyeLink 1000 **{EL1000}** is an eye tracker that allows to collect data about eye gaze and pupil size, it consists of a camera and an infrared light (SR Research Ltd, 2013); the 504 model **{ASL504}** composed of a camera and an infrared source, and the Applied Science Laboratories **{ASL4000}** 4000 series systems (e.g. 4000SU) allow eye tracking and pupil monitoring (Applied Science Laboratories, 2006)(LabX, 2017); the device known as Siemens Siregnost FD 5 **{SIREGNOSTFD5}** allows measuring ROS through forced oscillations (referenced by several researchers, e.g. (Gimeno, van der Weele, Koëter, de Monchy, & van Altena, 1993), (Pleger, Wilke, Glaser, Müller, & Vogel, 1989), etc.); Hans Rudolph (Rudolph & Pnt, 2004) flow head 3803 **{FH3803}** and the CS5 integrator **{GMCS5}** from GM Instruments (GM Instruments, 2015) as referenced by Ritz et al. (Ritz et al., 2000) for measuring VT and RR; the Finapres cuff (acronym for FINger Arterial PRESure (Imholz, Wieling, Van Montfrans, & Wesseling, 1998)) model IV **{FINAPRESS4}** from TNO Biomedical Instrumentation to measure HR, BP, SBP, and DBP continuously (renamed to Ohmeda 2300 Finapres BP monitor (Imholz et al., 1988) currently the technology has been applied in the Finapres NOVA (Finapres Medical Systems BV, 2012)); the Biosemi Active II **{ACTIVEII}** system measures signals from electrodes (e.g. Soleymani et al. collected EEG with 32 electrodes (Soleymani et al., 2013)) (Biosemi, n.d.); the Coulbourn S75-01 Hi Gain Bioamplifier **{S75-01}** and the Coulbourn S71-22 **{S71-22}** Skin Conductance Coupler, devices used by Vrana to collect ECG and EDA (Scott R. Vrana, 1993); BioPac provides devices for measuring or supporting physiological measurement (Biopac Systems Inc, 2017a) such as the MP100 **{MP100}** and MP150 **{MP150}** for context signal processing such as ECG, RESP, EDA, ST, etc. (since discontinued and replaced by the MP160 (Linton Instrumentation, 2011)), and the NIBP100D **{NIBP100D}** which is a system for non-invasive continuous monitoring of BP, SDP, DBP, PR, etc. (Biopac Systems Inc, 2017c) (Biopac Systems Inc, 2017e) (Toruzyme, 2001) (Blood & Monitoring, 2017) (Biopac Systems Inc, 2017d) (Fortin et al., 2006); the multiparametric device for vital sign quisition created by Murali et al. **{MURALI}**, is small and lightweight, composed of non-invasive electrodes and a chest strap, and contains a small computer that can continuously collect, process and store ECG, ICG, EDA and RESP data (Murali et al., 2015); the T-Sens GSR **{TGSR}** is a small device for measuring EDA through two electrodes placed on two fingertips (TEA, 2017); the g.MOBIlab+ **{MOBILAB}** is a portable system for multimodal acquisition of physiological signals (e.g. EEG, EMG, EOG, RESP, EDA, egc.) (Cornelissen & Waterman, 2016) (g.tec, 2017); Koralewski's Health Lab **{HEALTHLAB}** allows the collection of physiological context data (e.g. Lichtenstein et al. used to collect RESP through a chest strap, ST through a wrist strap, and ECG, EMG and EDA through electrodes (Lichtenstein, Antje; Oehme, 2008)) (Koralewski, n.d.); the FlexComp Infiniti **{FLEXCOMP}** from Thougth Technology Ltd. is an acquisition and monitoring system for physiological context signals (used by e.g. by Healey et al. (J. A. Healey & Picard, 2005)) (Thought Technology Ltd., 2016a); the Spacelabs 90207 **{S90207}** system enables ambulatory BP measurement (used by e.g. by Vrijkotte et al. (Vrijkotte et al., 2000)) (SpaceLabs Healthcare, 2008); the VU-MAS **{VU-MAS}** is an ambulatory monitoring system that allows the collection of physiological data (e.g. HR in Vrijkotte et al. (Vrijkotte et al.)) (Vrije Universiteit, n.d.).

RESEARCH	INSTRUMENTS & SENSORS	
	TECHNIQUES OBSTRUCTIONS	OTHER
Perdiz et al. (Perdiz et al., 2017)	{Undefined(EMG), Undefined(EOG)} (EMG, EOG).	<u>**Lightly obstructive T:**</u> {IMU} (HEAD).

Matlovic et al. (Matlovic et al., 2016)	{EPOC} (EEG) and {TGSR} (EDA).	**<u>Non-obstructive T:</u>** {FACEREADER, SHORE}. **(Q. INFORMAL)** {INFORMAL} (EMOTIONS). **(OTHER)** {TSTUDIO, CAPTIV}.
Z. Zhang et al. (Z. Zhang et al., 2016)	{MP150, NIBP100D} (BP(SBP, DBP), HR, PR, RESP(RR)) and {Undefined(EDA)} (EDA).	**<u>Non-obstructive T:</u>** {DI3D, A655SC, VIDEO} (HEAD, FACS, ST). **(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
Sano & Eng (Sano & Eng, 2016)	{Undefined(EEG)} (EEG), {Undefined(PSG)} (PSG), {Undefined(EOG)} (EOG), {Undefined(EMG)} (EMG) and {Undefined(MELAT)} (MELAT).	**<u>Non-obstructive T:</u>** {FUNF, APP} (LOCAL, CALL, SMS, SCREEN, APPS, EMAIL). **<u>Lightly obstructive T:</u>** {AFFECTIVAQ} (EDA, ST, ACC) and {MOTIONLOGGER} (ACC, LIGHT). **(Q. FORMAIS)** {SAME, PSQI} (SLEEP), {MBTI, BFIPT} (PERSON), {PSS} (STRESS), {SF-12} (HEALTH, CALM, ENERGY, MOOD) and {STAI} (ANXIETY). **(Q. INFORMAL)** {INFORMAL} (AGE, GENDER, FTF, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT).
Zhao et al. (Zhao et al., 2016)	{Undefined(ECG)} (ECG(HR)).	**<u>Non-obstructive T:</u>** {EQ-RADIO} (HR(IBI(RMSSD, SDNN)), RESP) and {VIDEO}. **(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
Basu et al. (Basu et al., 2016)	{ML870, FE116, ML135, ML309} (EDA, ST) and {Undefined(EMG)} (EMG).	**<u>Lightly obstructive T:</u>** {BIOHARNESS} (ECG, HR, PR, RESP(RR)). **(OTHERS)** {LABCHART}.
Aracena et al. (Aracena et al., 2016)	{EL1000} (PUPIL, GAUZE).	
Murali et al. (Murali et al., 2015)	{MURALI} ((ECG, ICG)(PEP, PTT), NIBP, EDA, RESP(RR)).	
Cruz et al. (Cruz et al., 2015)	{MOBILAB} (EOG).	
Matiko et al. (Matiko et al., 2014)	{Undefined(EEG)} (EEG).	**(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
Soleymani et al. (Soleymani et al., 2013)	{ACTIVEII} (EEG).	**<u>Non-obstructive T:</u>** {VIDEO} (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH). **(OTHERS)** {OBSERVATION} (EMOTIONS).
Alzoubi et al. (Alzoubi et al., 2013)	{MP150} (ECG(HRV), EMG, EDA, RESP).	**(Q. FORMAIS)** {AFFECTGRID} (EMOTIONS). **(OTHERS)**

		{ACQK}.
Nawasalkar et al. (Nawasalkar et al., 2013)	{Undefined(NIBP), Undefined(RESP)} (NIBP, RESP(RR)).	
Murad & Malkawi (Murad & Malkawi, 2012)	{Undefined(EEG), Undefined(HR), Undefined(HRV), Undefined(PEP), Undefined(SV), Undefined(BP), Undefined(RESP), Undefined(EDA), Undefined(nSRR), Undefined(ST)} (EEG, HR, HRV, PEP, SV, BP(SBP, DBP), RESP(VT, ROS, RR), EDA, nSRR, ST).	
C. Y. Chang et al. (Chang et al., 2012)	{ML870} (ECG, BVP, PR, EDA).	**(Q. FORMAIS)** {SAM} (EMOTIONS).
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	{ML870} (ECG(HRV), PPG).	**<u>Non-obstructive T:</u>** {VIDEO} (PUPIL).
Y. Liu et al. (Y. Liu et al., 2010)	{EPOC} (EEG).	**(Q. FORMAIS)** {SAM} (EMOTIONS). **(Q. INFORMAL)** {INFORMAL} (EMOTIONS). **(OTHERS)** {EPOC-SDK}.
J. Kim & Andre (J. Kim & André, 2008)	{PROCOMP} (EMG, EDA, ECG(HR, HRV), RESP(RR, BRV)).	
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	{HEALTHLAB} (RESP(RR, RDEP), EDA, ECG(HR, HRV, IBI), EMG, ST).	**(Q. FORMAIS)** {SAM} (EMOTIONS). **(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	{ASL504} (PUPIL), {S71-22} (EDA) and {S75-01} (ECG(HR, IBI)).	
Mandryk & Atkins (Mandryk & Atkins, 2007)	{PROCOMP} (EDA, ECG(HR), EMG).	**<u>Non-obstructive T:</u>** {VIDEO, AUDIO}. **(Q. INFORMAL)** {INFORMAL} (EMOTIONS). **(OTHERS)** {BIOGRAPH}.
Zhai & Barreto (Zhai & Barreto, 2006)	{Undefined(EDA), Undefined(BVP), Undefined(PUPIL), Undefined(ST), Undefined(LIGHT), Undefined(TEMP)} (EDA, BVP(IBI), PUPIL, ST, LIGHT**, TEMP***). *** data not used in the correlation	
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	{FLEXCOMP} (ECG(HR, HRV), EMG, EDA, RESP).	**<u>Non-obstructive T:</u>** {VIDEO}. **(Q. INFORMAL)** {INFORMAL} (STRESS). **(OTHERS)**

		{OBSERVATION} (STRESS).
Herbon et al. (Herbon et al., 2005)	{Undefined(EDA), Undefined(ST), Undefined(HR)} (EDA, ST, HR).	**Lightly obstructive T:** {HERBON} (PUPIL). **(Q. FORMAIS)** {SAM} (EMOTIONS). **(Q. INFORMAL)** {INFORMAL} (GENDER, AGE, HEALTH, TECHEXPERT).
Partala et al. (Partala et al., 2005)	{MODEL15} (EMG).	**(Q. INFORMAL)** {INFORMAL} (EMOTIONS). **(OTHERS)** {LINK15}.
Van Eck et al. (van Eck et al., 2005)	{CORTISOL, SALIVETTE} (CORT).	**(Q. FORMAIS)** {PSS} (STRESS), {LTE} (LIFEEVENTS), {LDI} (DIFFICULTIES), {PSC} (HEALTH), {SDS} (DEPRESSION), {STAI} (ANXIETY) and {STAS} (ANGER). **(Q. INFORMAL)** {INFORMAL} (MOOD, WELLBEING, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH, EMOTIONS).
K. H. Kim et al. (K. H. Kim et al., 2004)	{MP100} (ECG(HR,HRV), PPG, ST, EDA).	**(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
Haag et al. (Haag et al., 2004)	{PROCOMP} (EMG, EDA, ST, PPG(BVP(HR)), ECG(HR), RESP).	
Partala & Surakka (Partala & Surakka, 2003)	{ASL4000} (PUPIL).	**(Q. INFORMAL)** {INFORMAL} (EMOTIONS). **(OTHERS)** {PSYSCOPE}.
C J Harmer et al. (C J Harmer et al., 2003)	{MANUAL}*** (SEROT). *** citalopram administration (WebMD Drugs & Medications, 2017a).	**(Q. FORMAIS)** {BFS} (MOOD). **(Q. INFORMAL)** {INFORMAL} (EMOTIONS, ENERGY, ANXIETY). **(OTHERS)** {INTERVIEW}.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	{ORION, SALIVETTE}*** (CORT) and {Undefined(EMG)} (EMG). *** hydrocortisone administration (WebMD Drugs & Medications, 2017b)	**(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
Jennifer a Healey (Jennifer a Healey et al., 2000)	{PROCOMP} (EDA, PPG(BVP(HR)), EMG, RESP) and {Undefined(ECG)} (ECG(HR, HRV)).	**(Q. INFORMAL)** {INFORMAL} (STRESS).
Vrijkotte et al. (Vrijkotte et al., 2000)	{S90207} (BP(SBP, DBP)) and {VU-MAS} (ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC).	**(Q. FORMAIS)** {ERI} (STRESS) and {POMS} (MOOD). **(Q. INFORMAL)** {INFORMAL} (PERSON, AGE, WORKYEARS, ACADDG, PHYSI, BMI, HEIGHT, WEIGHT, WAIST, CAFFEI, ALCOH, SMOKING).
Ritz et al. (Ritz et al., 2000)	{SIREGNOSTFD5} (ROS), {FH3803, GMCS5} (VT, RR), {FINAPRESS4} (HR, BP(SBP, DBP)) and {Undefined(EDA)} (EDA).	**(Q. FORMAIS)** {SAM} (EMOTIONS), {AIM, TAS, MCSDS}. **(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
J. Healey & Picard	{PROCOMP} (EDA, PPG(BVP(HR)), RESP, EMG).	

(J. Healey & Picard, 1998)		
Rajita Sinha (Rajita Sinha, 1996)	{78B} (BP(SBP, DBP)) and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} (ECG(HR), EDA, ST, EOG, EMG).	**(Q. FORMAIS)** {MMPI, QMI, TAS, BDI, STAI} and {DES} (EMOTIONS). **(Q. INFORMAL)** {INFORMAL} (EMOTIONS). **(OTHERS)** {INTERVIEW}.
Scott R. Vrana (Scott R. Vrana, 1993)	{S75-01} (ECG(HR)), {Undefined(EMG)} (EMG) and {S71-22} (EDA).	**(Q. FORMAIS)** {QMI}. **(Q. INFORMAL)** {INFORMAL} (EMOTIONS).
R Rinha et al. (R Sinha et al., 1992)	{Undefined(BP)} (BP(SBP, DBP)), {Undefined(ICG)} (ICG(SV, CO, PVR, PEP, LVET)), {Undefined(ECG)} (ECG(HR)) and Undefined(PCG)} (PCG).	**(Q. FORMAIS)** {QMI, TAS} and DES} (EMOTIONS), **(OTHERS)** {INTERVIEW, OBSERVATION}.

() represents a raw signal; and {} an instrument.

3.1.4. Analysis

Technology still has a long way to go to promote collection with low or no obstructivity. Ideally, it should be possible to inspect the entire context freely (i.e. completely unobtrusively), unperceivable to users, and the data should be transmitted to the processing units in real time with total absence of cabling (Ouwerkerk et al., 2008). For now, researchers are designing their emotional detection systems using existing instruments and sensors (Ouwerkerk et al., 2008).

The non-obtrusive techniques identified in the literature focus essentially on collecting and processing VIDEO and AUDIO. The major advantage of these techniques is the reuse of instruments that already exist in users' everyday life. However, they are not immune to the problems and challenges already listed in the section on context variables related to facial expression (cf. use of adornments (Cruz et al., 2015) (H. Wang et al., 2010), age, gender, and cultural insensitivity (Rani & Sarkar, 2006), and masking (J. Kim & Andre, 2008) (Y. Liu et al., 2010)). However they are techniques that tend to fade into the user's background (Weiser & Brown, 1996). Thus, given the legal and ethical constraints on capturing images and sound of people, this will be a viable way of introspecting the user's context, especially if the data is collected with their oblivion.

Still regarding non-obstructive techniques, the smartphone is the most used instrument for social context data collection. There are several advantages in reusing this instrument for context data collection: it is an instrument that is used daily in a natural and widespread way by people (Eckert et al., 2016) (N. D. Lane et al., 2010); there is no need to change device usage patterns to generate new information, because the data to be collected already exists on the device naturally; and the raw data collected directly and objectively represents social interactions. However, not all people use smartphones (e.g. older people may use more basic phones) and the processing characteristics of each device must be taken into account when analyzing obstructivity caused by logging applications. Besides the ethical issues regarding the collection of user data, smartphone use also has other contraindications: excessive usage time can cause ANXIETY and insomnia (Cheever, Rosen, Carrier, & Chavez, 2014) which can lead in the long run to DEPRESSION (Thomée, Härenstam, & Hagberg, 2011); and exposure to light from screens at the end of the day can suppress MELAT secretion, increasing the level of alertness (Chellappa et al., 2011) (Sano & Eng, 2016).

Techniques classified as low obstructive are essentially based on the use of wristbands and small context data collection devices. The main advantage will be the possibility of collecting physiological context signals with devices that represent low obstructivity. As there is not much technology yet available to collect this type of signals in a non-obstructive way, all that remains is to use devices whose use becomes transparent and forgotten over time, promoting, as much as possible, the quality and integrity of the data collected (Weiser, 1991) (Weiser & Brown, 1996). Although unobtrusive, the regular use of these devices depends on the forgetfulness of the user. Since this is not an everyday device such as smartphones, forgetfulness can interrupt data collection, compromising the success and validity of emotional detection systems. Perhaps the development of Smart Textiles technology will contribute to solving the problem. The use of literally wearable sensors (Haag et al., 2004) could bring the necessary naturalness and transparency to the process of collecting physiological context data as is currently the case with smartphones context (Capineri, 2014) (M. Chan, Estève, Fourniols, Escriba, & Campo, 2012).

Although an effort by researchers to use devices with little or no obstructivity has been noted in the recent past, there are many devices used in research on emotional detection with obstructivity. These are devices whose implementation in real life would be difficult because of the constraints to their use, either because they are used only in laboratories or clinical environments, or because they imply the alteration of people's normal daily lives. With technological evolution and the miniaturization of sensors, it is expected that the number of obstructive devices will continue to decrease. However, until this happens, the possible impartiality of the data collected through these instruments must be considered.

It is expected that the technological evolution of contactless sensors will allow the reduction of the obstructiveness of the devices and the possibility of daily collection in real environments (Ouwerkerk et al., 2008). In the meantime, some researchers have been pointing out creative strategies to decrease the obstructiveness of existing sensors: Schumm et al., Ouwerkerk et al., Lim et al. and Steffen et al. have installed obstructive sensors on bench seats to measure physiological signals (e.g. ECG) while people are seated (Schumm & Arnrich, 2012) (Ouwerkerk et al., 2008) (Lim, Kim, & Park, 2006) (Steffen & Leonhardt, 2008); Zakrezwski et al. and Suzuki et al. studied the hypothesis of detecting HR through radar systems (Zakrzewski, Kolinummi, & Vanhala, 2006) (Suzuki et al., 2008), in other words, without the need to use obstructive techniques; Schumm et al. thought of integrating electrodes in the socks to measure ECG and AGE in the lower limbs (textile sensor integration) thus avoiding the placement of obstructive collection sensors on the fingers (Schumm et al., 2010); Zhao et al. created the EQ-RADIO that can detect heartbeats from the reflection of the WiFi signal (Zhao et al., 2016); etc.

RESEARCH	TECHNICAL NO OBSTRUCTIONS	FEW TECHNIQUES OBSTRUCTIONS	TECHNIQUES OBSTRUCTIONS	OTHER
Perdiz et al. (Perdiz et al., 2017)		{IMU} *(HEAD)*.	{Undefined(EMG), Undefined(EOG)} *(EMG, EOG)*.	
S. H. Lee et al. (S. H. Lee et al., 2016)	{VIDEO} *(FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, NOSE, LIPS, CHEEKS, JAW, MOUTH)*.			

Eckert et al. (Eckert et al., 2016)	{APP, PICTURES} *(FACS, CAUL, EYES, EYEBROWS, NOSE, MOUTH*).			
Matlovic et al. (Matlovic et al., 2016)	{FACEREADER, SHORE}.		{EPOC} *(EEG)* and {TGSR} *(EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {TSTUDIO, CAPTIV}.
Gogia et al. (Gogia et al., 2016)	{KINECT, VIDEO} *(HEAD)*.	{MINDWAVE} *(EEG)*.		**(OTHERS)** {MINDWAVE-SDK, KINECT-SDK}.
Z. Zhang et al. (Z. Zhang et al., 2016)	{DI3D, A655SC, VIDEO} *(HEAD, FACS, ST)*.		{MP150, NIBP100D} *(BP(SBP, DBP), HR, PR, RESP(RR)) and* {Undefined(EDA)} *(EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Sano & Eng (Sano & Eng, 2016)	{FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*.	{AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*.	{Undefined(EEG)} *(EEG)*, {Undefined(*PSG*)} *(PSG)*, *{Undefined(*EOG)} *(EOG)*, {Undefined(*EMG*)} *(EMG)* and {Undefined(MELAT)} *(MELAT)*.	**(Q. FORMAIS)** {SAME, PSQI} *(SLEEP)*, {MBTI, BFIPT} *(PERSON)*, {PSS} *(STRESS)*, {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*. **(Q. INFORMAL)** {INFORMAL} *(AGE, GENDER, FTF, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*.
Zhao et al. (Zhao et al., 2016)	{EQ-RADIO} *(HR(IBI(RMSSD, SDNN)), RESP) and* {VIDEO}.		{Undefined(ECG)} *(ECG(HR))*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Zenonos et al. (Zenonos et al., 2016)		{SILMEEW2X, SILMEEBTYPE} *(ECG(HR(IBI(RMSSD, SDNN)), HRV), PPG(PR, PTT), ST)*.		**(Q. FORMAIS)** {HEALTHYOFFICE} *(MOOD, EMOTIONS)*. **(OTHERS)** {HRVAS} *(HRV)* and {HAR} *(ACC)*.
Basu et al. (Basu et al., 2016)		{BIOHARNESS} *(ECG, HR, PR, RESP(RR))*.	{ML870, FE116, ML135, ML309} *(EDA, ST)* and {Undefined(EMG)} *(EMG)*.	**(OTHERS)** {LABCHART}.
Aracena et al. (Aracena et al., 2016)			{EL1000} *(PUPIL, GAUZE)*.	
Adams & Robinson	{FACETRACKER} *(FACS (HEAD,*			

(Adams & Robinson, 2015)	*EYELIDS, EYEBROWS, CHEEKS, EYES, NOSE, WRINKLES, LIPS, CHIN, JAW), GAZE)*.			
Turan et al. (Turan et al., 2015)	{PICTURES, VIDEO} *(FACE, EYES).*			
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	{AUDIO} *(SPEECH, VOLUME)*.			
Lalitha et al. (Lalitha et al., 2015)	{AUDIO} *(SPEECH, PITCH and VOLUME)*.			
Singh et al. (Singh et al., 2015)	{VIDEO} *(SHOULDERS, HANDS)*.			
Murali et al. (Murali et al., 2015)			{MURALI} *((ECG, ICG)(PEP, PTT), NIBP, EDA, RESP(RR))*.	
Jaques et al. (Jaques et al., 2015)	{APP} *(CALL, SMS, SCREEN, LOCAL).*	{AFFECTIVAQ} *(EDA, ST, ACC)*		**(Q. INFORMAL)** {INFORMAL} *(HAPPY, ACADCL, ACADEX, ACADST, PHYSI, SOCIAL, CAFFEI, ALCOH, DRUGS, STRESS, HEALTH, ENERGY, ALERT, CALM, SLEEP, NAP)*.
Cruz et al. (Cruz et al., 2015)			{MOBILAB} *(EOG)*.	
Saha et al. (Saha et al., 2014)	{KINECT} *(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN, ACC).*			**(OTHERS)** {KINECT-SDK}.
Matiko et al. (Matiko et al., 2014)			{Undefined(EEG)} *(EEG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Bogomolov et al. (Bogomolov et al., 2014)	{APP} *(CALL, SMS, PROXIMITY)* and {EXISTINGDATA} *(WEATHER)*.			**(Q. FORMAIS)** {BFIPT} *(PERSON)*. **(Q. INFORMAL)** {INFORMAL} *(STRESS)*.
Agrawal et al. (Agrawal et al., 2013)	{VIDEO} *(EYES, MOUTH, LIPS, SKIN)*.			
Soleymani et al. (Soleymani et al., 2013)	{VIDEO} *(HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH)*.		{ACTIVEII} *(EEG)*.	**(OTHERS)** {OBSERVATION} *(EMOTIONS)*.
Vermun et al. (Vermun et al., 2013)	{KINECT} *(HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP, KNEES)*.			
Kusserow et al. (Kusserow et al., 2013)		{TALKASSIST} *(HR(HRV), EDA, ACC, ST)*, {KUSSEROW2} *(ECG(HR), ACC)*, {KUSSEROW3}		**(Q. INFORMAL)** {INFORMAL} *(STRESS, MOOD)*.

		(ECG(HR), ACC) and {KUSSEROW4} *(HR, ACC)*.		
Alzoubi et al. (Alzoubi et al., 2013)			{MP150} *(ECG(HRV), EMG, EDA, RESP)*.	**(Q. FORMAIS)** {AFFECTGRID} *(EMOTIONS)*. **(OTHERS)** {ACQK}.
Nawasalkar et al. (Nawasalkar et al., 2013)			{Undefined(NIBP), Undefined(RESP)} *(NIBP, RESP(RR))*.	
Sano & Picard (Sano & Picard, 2013b)		{AFFECTIVAQ} *(EDA, ACC)* and {FUNF} *(CALL, SMS, LOCAL, SCREEN)*.		**(Q. FORMAIS)** {PSS} *(STRESS)*, {PSQI} *(SLEEP)* and {BFIPT} *(PERSON)*. **(Q. INFORMAL)** {INFORMAL} *(SLEEP, ELECTR,* HEALTH, MOOD, ALERT, TIRED, STRESS, NAP, CAFFEI, ALCOH*)*.
Raudonis (Raudonis, 2013)		{RAUDONIS1} *(GAZE, EYES, PUPIL)*.		
Kawai et al. (Kawai et al., 2013)	{XCEI30} *(PUPIL)*.			**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {DS400}.
Babiker et al. (Babiker et al., 2013)	{TX300} *(EYES, GAZE, PUPIL)*.			**(Q. FORMAIS)** {PANES-X} *(EMOTIONS)*.
LikamWa et al. (LiKamWa et al., 2013)	{MOODSCOPE} *(SMS, EMAIL, CALL, APPS, BROWSER, LOCAL)*.			**(Q. FORMAIS)** {CIRCUMPLEX} *(MOOD)*.
Murad & Malkawi (Murad & Malkawi, 2012)			{Undefined(EEG), Undefined(HR), Undefined(HRV), Undefined(PEP), Undefined(SV), Undefined(BP), Undefined(RESP), Undefined(EDA), Undefined(nSRR), Undefined(ST)} *(EEG, HR, HRV, PEP, SV, BP(SBP, DBP), RESP(VT, ROS, RR), EDA, nSRR, ST)*.	
C. Y. Chang et al. (Chang et al., 2012)			{ML870} *(ECG, BVP, PR, EDA)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*.
Bauer & Lukowicz (Bauer & Lukowicz, 2012)	{APP} *(LOCAL, PROXIMITY, CALL, SMS)*.			
Yang & Bhanu (S. Yang & Bhanu, 2011)	{VIDEO} *(HEAD, FACE)*.			**(OTHERS)** {EAI}.

Dhall et al. (Dhall et al., 2011)	{PICTURES, VIDEO} *(FACE)*.			
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	{VIDEO} *(PUPIL)*.		{ML870} *(ECG(HRV), PPG)*.	
Hernandez et al. (Hernandez et al., 2011)	{EXISTINGDATA} *(CALL)*.	{AFFECTIVAQ} *(EDA)*.		**(Q. INFORMAL)** {INFORMAL} *(STRESS)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
N. Lane et al. (N. Lane et al., 2011)	{BEWELL} *(SLEEP, PHYSI, TALK, LOCAL, ACC)*.			**(Q. INFORMAL)** {INFORMAL} *(DEPRESSION, SLEEP, WELLBEING)*. **(OTHERS)** {HAR}.
H. Wang et al. (H. Wang et al., 2010)	{VIDEO} *(EYES)*.			
Bos (Bos, 2010)		{BQPET} *(EEG)*.		**(OTHERS)** {BIOEXPLORER}.
Y. Liu et al. (Y. Liu et al., 2010)			{EPOC} *(EEG)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {EPOC-SDK}.
Setz et al. (Setz et al., 2010)		{EMOTIONBOARD} *(EDA)*.		
J. Kim & Andre (J. Kim & André, 2008)			{PROCOMP} *(EMG, EDA, ECG(HR, HRV), RESP(RR, BRV))*.	
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)			{HEALTHLAB} *(RESP(RR, RDEP), EDA, ECG(HR, HRV, IBI), EMG, ST)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)			{ASL504} *(PUPIL)*, {S71-22} *(EDA)* and {S75-01} *(ECG(HR, IBI))*.	
Gunes & Piccardi (Gunes & Piccardi, 2007)	{VIDEO} *(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, CHEEKS, FOREHEAD, JAW, NOSE, HANDS, FINGERS, FISTS, PALMS, SHOULDERS, NECK)*.			
Castellano et al. (Castellano et al., 2007)	{VIDEO} *(ARMS)*.			

Mandryk & Atkins (Mandryk & Atkins, 2007)	{VIDEO, AUDIO}.		{PROCOMP} *(EDA, ECG(HR), EMG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*. **(OTHERS)** {BIOGRAPH}.
Sebe et al. (Sebe et al., 2006)	{VIDEO} *(HEAD, EYEBROWS, EYELIDS, MOUTH)* and {AUDIO} *(VOLUME, SPEECH, PITCH)*.			
Zhai & Barreto (Zhai & Barreto, 2006)			{Undefined(EDA), Undefined(BVP), Undefined(PUPIL), Undefined(ST), Undefined(LIGHT), Undefined(TEMP)} *(EDA, BVP(IBI), PUPIL, ST, LIGHT, TEMP)*.	
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	{VIDEO}.		{FLEXCOMP} *(ECG(HR, HRV), EMG, EDA, RESP).*	**(Q. INFORMAL)** {INFORMAL} *(STRESS)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
Herbon et al. (Herbon et al., 2005)		{HERBON} *(PUPIL)*.	{Undefined(EDA), Undefined(ST), Undefined(HR)} *(EDA, ST, HR)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(GENDER, AGE, HEALTH, TECHEXPERT)*.
Partala et al. (Partala et al., 2005)			{MODEL15} *(EMG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).* **(OTHERS)** {LINK15}.
Van Eck et al. (van Eck et al., 2005)			{CORTISOL, SALIVETTE} *(CORT)*.	**(Q. FORMAIS)** {PSS} *(STRESS)*, {LTE} *(LIFEEVENTS),* {LDI} *(DIFFICULTIES),* {PSC} *(HEALTH),* {SDS} *(DEPRESSION)*, {STAI} *(ANXIETY)* and {STAS} *(ANGER)*. **(Q. INFORMAL)** {INFORMAL} *(MOOD, WELLBEING, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH, EMOTIONS).*
Busso et al. (Busso et al., 2004)	{VIDEO} *(FOREHEAD, EYEBROWS, EYES, CHEEKS) and* {AUDIO} *(PITCH, VOLUME)*.			
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		{JAWBONE} *(EDA, HR, ST)*.		**(Q. INFORMAL)**

				{INFORMAL} *(AGE, GENDER, ETHNICITY, EMOTIONS)*.
K. H. Kim et al. (K. H. Kim et al., 2004)			{MP100} *(ECG(HR,HRV), PPG, ST, EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*
Haag et al. (Haag et al., 2004)			{PROCOMP} *(EMG, EDA, ST, PPG(BVP(HR)), ECG(HR), RESP)*.	
Partala & Surakka (Partala & Surakka, 2003)			{ASL4000} *(PUPIL)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).* **(OTHERS)** {PSYSCOPE}.
C J Harmer et al. (C J Harmer et al., 2003)			{MANUAL} *(SEROT)*.	**(Q. FORMAIS)** {BFS} *(MOOD)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS, ENERGY, ANXIETY).* **(OTHERS)** {INTERVIEW}.
Nwe et al. (Nwe et al., 2001)	{AUDIO} *(SPEECH)*.			
Buchanan & Lovallo (Buchanan & Lovallo, 2001)			{ORION, SALIVETTE} *(CORT)* and {Undefined(EMG)} *(EMG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*
Jennifer a Healey (Jennifer a Healey et al., 2000)			{PROCOMP} *(EDA, PPG(BVP(HR)), EMG, RESP)* and {Undefined(*ECG*)} *(ECG(HR, HRV))*.	**(Q. INFORMAL)** {INFORMAL} *(STRESS).*
Vrijkotte et al. (Vrijkotte et al., 2000)			{S90207} *(BP(SBP, DBP))* and {VU-MAS} *(ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC)*.	**(Q. FORMAIS)** {ERI} *(STRESS)* and {POMS} *(MOOD)*. **(Q. INFORMAL)** {INFORMAL} *(PERSON, AGE, WORKYEARS, ACADDG, PHYSI, BMI, HEIGHT, WEIGHT, WAIST, CAFFEI, ALCOH, SMOKING)*.
Ritz et al. (Ritz et al., 2000)			{SIREGNOSTFD5} *(ROS)*, {FH3803, GMCS5} *(VT, RR)*, {FINAPRESS4} *(HR, BP(SBP, DBP))* and {Undefined(EDA)} *(EDA)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*, {AIM, TAS, MCSDS}. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
L. S. Chen et al. (L. S. Chen et al., 1998)	{AUDIO} *(SPEECH, PITCH)* and {VIDEO} *(EYES, EYEBROWS,*			

	MOUTH, WRINKLES, FROWN).			
J. Healey & Picard (J. Healey & Picard, 1998)			{PROCOMP} *(EDA, PPG(BVP(HR)), RESP, EMG).*	
Rajita Sinha (Rajita Sinha, 1996)			{78B} *(BP(SBP, DBP))* and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} *(ECG(HR), EDA, ST, EOG, EMG).*	**(Q. FORMAIS)** {MMPI, QMI, TAS, BDI, STAI} and {DES} *(EMOTIONS).* **{Q. INFORMAL)** {INFORMAL} *(EMOTIONS).* **{OTHER)** {INTERVIEW}.
Scott R. Vrana (Scott R. Vrana, 1993)			{S75-01} *(ECG(HR))*, {Undefined(*EMG*)} *(EMG)* and {S71-22} *(EDA).*	**(Q. FORMAIS)** {QMI}. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*
R Rinha et al. (R Sinha et al., 1992)			{Undefined(BP)} *(BP(SBP, DBP)), {Undefined(*ICG)} *(ICG(SV, CO, PVR, PEP, LVET)),* {Undefined(ECG)} *(ECG(HR))* and Undefined(PCG)} *(PCG).*	**(Q. FORMAIS)** {QMI, TAS} and {DES} *(EMOTIONS).* **{OTHER)** {INTERVIEW, OBSERVATION}.

() represents a raw signal; and {} an instrument.

3.2. SUBJECTIVE MEASUREMENT

Behavioral science researchers use questionnaires and observation as measurement techniques, and make very little use of technology (Rachuri et al., 2010). Questionnaires are subjective measurement instruments (Kusserow et al., 2013), are interesting for understanding users' attitudes (R. Pagulayan et al., 2012), and are widely used in emotional assessment (Fulton & Medlock, 2003) (Mandryk & Atkins, 2007). They also allow for easier generalization and statistical analysis (Mandryk et al., 2006) questionnaires collect direct information of what is to be assessed, although the subjectivity of responses can lead to erroneous measurements and incorrect results (Caballe, 2015) (Sano & Eng, 2016) (Johnston et al., 2009). Still questionnaires are accepted by the literature as ways to measure emotions (Babiker et al., 2013).

The questionnaires commonly used for emotional detection are self-administered or administered by experts, and can be divided into two types: verbal questionnaires, i.e. those consisting of questions (cf. sentences or words) (e.g. SF-12 (Ware, Kosinski, & Keller, 1996), PANAS-X (David Watson & Clark, 1999)); and the nonverbal recall ones that are answered based on images with the goal of decreasing the subjectivity of textual interpretation (e.g. SAM (Margaret M. Bradley & Lang, 1994) and **PREMO** (P. Desmet, 2003)) (Babiker et al., 2013).

Each human being may react differently to the same emotional stimulus (Raudonis, 2013) (e.g. the physiological reaction to an event may differ between people (Manuck et al., 1991)). Past experience, environment, and personality make each person unique, justifying the difference in their emotional responses (Bos, 2010). It is in this context that questionnaires can be an important tool for emotional recognition systems (Bos, 2010). Through questionnaires, the collection of context data can be achieved in a more compatible and comparable way across individuals, as the respondent can answer at a level of greater abstraction of their personal specificity.

Researchers have used questionnaires in several ways: i) to support the screening process (e.g. Rajita Sinha used the QMI and the TAS to assess the candidates' ability to interpret images and express their emotions (Rajita Sinha, 1996), van Eck et al. used the PSS to select participants (van Eck et al., 2005), etc.); ii) collection of context data for correlation with other variables; and iii) collection of ground truth data (e.g. Chen et al., Zenonos et al. and Sano et al. used questionnaires to collect ground truth (Z. Chen et al., 2013) (Zenonos et al., 2016) (Sano & Picard, 2013b). Some authors have chosen to replace ground truth collection with the use of databases of images, sounds, or videos pre-labeled with the emotions they elicit (e.g. International Affective Picture System (IAPS) (P.J. Lang, Bradley, & Cuthbert, 2005), International Affective Digitized Sounds (IADS) (M.M. Bradley & Lang, 1999), etc.).

The issue of obstructiveness could also be raised in the analysis of the questionnaires. However, as their application is time-scalable and they are typically answered at the beginning or end of experimental cycles, it was decided not to address the obstructiveness of these instruments. Still, some researchers have chosen to digitize the questionnaire in order to facilitate the respondent response process. For example: Chittaranjan et al. implemented the BFIPT in a smartphone application (Chittaranjan, Jan, & Gatica-Perez, 2011); and Zenonos et al. created a smartphone questionnaire to collect user mood based on quantifying various emotions felt by the user (Zenonos et al., 2016).

Many researchers use statistically validated questionnaires, whose scientific recognition is proven by the successive reuses in other investigations (e.g. SAM (Margaret M. Bradley & Lang, 1994), PSS (S. Cohen, Kamarck, & Mermelstein, 1983), etc.). However, some researchers also use questionnaires more informally (e.g. the end-of-study questionnaire by Sano et al. (Sano & Eng, 2016)). In this context we decided to also divide the questionnaires present in the reviewed literature. Initially, we present the formal questionnaires whose validity is proven by the different reuses in various investigations, followed by the other questionnaires for which we did not find reuse in other investigations or academic evidence to prove their formality (i.e. questionnaires purposely designed to meet specific information needs of the research where they appear).

3.2.1. Formal questionnaires

In this section, statistically validated questionnaires are analyzed, i.e. those whose reuse by several researchers provides scientific validity. In addition to the questionnaires present in the investigations analyzed for collecting context and ground truth data (cf. verbal and nonverbal), questionnaires used in screening processes, or others that may be useful for collecting context data for emotional detection, are also discussed.

There are several **verbal** response questionnaires used: the Perceived Stress Scale **{PSS}** is one of psychology's most widely used instruments to measure the perception of STRESS (S. Cohen et al., 1983); the Effort-Reward Imbalance **{ERI}** is a questionnaire used to measure chronic work-related STRESS (Vrijkotte et al., 2000) by assessing effort, reward, and overcoming (Siegrist et al., 2004); the Long-term Difficulties Inventory **{LDI}** (Hendriks, Ormel, & van de Willige, 1990) provides an assessment of daily difficulties (DIFFICULTIES) (e.g. problems at work, school, home, personal finances, social relationships with network members, etc.) and is used in the assessment of chronic stress (Rosmalen, Bos, & de Jonge, 2012); the Psychosomatic Symptom Checklist **{PSC}** (Attanasio, Andrasik, Blanchard, & Arena, 1984) used to assess people's usual health complaints (HEALTH) (e.g. head and back pain, nausea, etc. (van Eck et al., 2005)); the Short-Form 12 **{SF-12}** (shortened version of the Short-Form 36 (SF-36)) is an instrument that measures quality of life related to physical and mental health (HEALTH) (Sano & Eng, 2016), and is composed of questions related to feeling CALM, energy, DEPRESSION, and ANXIETY (Ware et al., 1996); the Zung Self-rating Depression Scale **{SDS}** is a technique for assessing people's level of DEPRESSION (ZUNG, 1965) the Beck Depression Inventory **{BDI}** (currently in its second version (BDI-II) (Beck,A.T.;Steer,R.A,Brown, 1996)) is one of the most widely used instruments to assess DEPRESSION (Gorestein, 1998)), in which the respondent indicates the intensity of a set of items that measure attitudes and symptoms related to depression (Leonetti & Foderaro, 2007) (Aaron T. Beck, 1967); Spielberger's State-Trait Anxiety Inventory **{STAI}** allows measuring ANXIETY (Spielberger CD, 1983) (Cd Spielberger, Gorsuch, Lushene, & Vagg, 1983); also by the same author, Spielberger State-Trait Anger Scale **{STAS}** is a scale to measure ANGER and, together with Anger Expression (AX), gave rise to the State-Trait Anger Expression Inventory (STAXI) (C. D. Spielberger, 2010a) (C. D. Spielberger, 2010b); the Pittsburgh Sleep Quality Index **{PSQI}** is an instrument to measure sleep quality and patterns (SLEEP) (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989); the Big Five Inventory Personality Test **{BFIPT}** is an inventory that measures the five dimensions of a person's personality (cf. Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to experience) (McCrae & John, 1992) (John, O. P., & Srivastava, 1999); the Myers Briggs Type Indicator **{MBTI}** is an instrument used to measure and categorize personalities and behavior (Briggs, 2015) (Myers & Briggs, n.d.) (C. Reis, 2016); the Positive And Negative Affect Schedule **{PANAS}** is based on the idea that it is possible for someone to feel something positive and negative simultaneously (LiKamWa et al., 2013) (J. T. Larsen, Mcgraw, & Cacioppo, 2001), it is based on a list of words that describe different feelings and emotions (representing the dimensions: Positive Affect (PA); and Negative Affect (NA)), which the respondent should rate on a five-point scale representing the intensity felt in each emotion (EMOTIONS) (D Watson, Clark, & Tellegen, 1988); the Positive And Negative Affect Schedule - Exapanded Form **{PANAS-X}** is an expanded version of PANAS that adds a second level of mood assessment with the measurement of eleven specific emotions considered by psychologists to be basic emotions (Babiker et al., 2013) (cf. fear, sadness, guilt, hostility, shyness, fatigue, surprise, joviality (good mood), self-confidence, alertness, and serenity) (EMOTIONS) (David Watson & Clark, 1999); the Profile Of Mood States {POMS} (McNair, Lorr, & Droppleman, 1989) is composed of several emotion-related adjectives and assesses mood (MOOD) through feeling tense, depressed, angry, vigorous, fatigued, and confused (Sano & Eng, 2016); the Befindlichkeits Scale **{BFS}**, also known as the Zerssen Mood Scale consists of emotion-related adjectives and is used to collect the mood (MOOD) of respondents (Heimann, Bobon-Schrod, Schmocker, & Bobon, 1975) (C J Harmer et al., 2003) (von Zerssen, Strian, & Schwarz, 1974); HealthyOffice **{HEALTHYOFFICE}** is a smartphone application presented by Zenonos et al. designed to facilitate mood self-reporting (MOOD) from entering the intensity of emotions felt by the user (the application was created under the European IES Cities project and includes a reminder system for filling in) (KWMC, 2016) (IES Cities Project, 2016) (Zenonos et al., 2016); the Beck Depression Inventory **{BDI}** (currently in version 2 (BDI-II) (Beck,A.T.;Steer,R.A,Brown, 1996)) is one of the most widely used instruments to assess DEPRESSION (Gorestein, 1998)), in which the respondent rates the intensity felt relative to a set of items for measuring attitudes and symptoms related to depression (Leonetti & Foderaro, 2007) (Aaron T.Beck, 1967); the List of Threatening Experiences **{LTE}** questionnaire, also referred to in the literature as LTE-Q to differentiate Brugha et al.'s list of threats from the questionnaire (Q) that uses this list (T. S. Brugha & Cragg, 1990), assesses the key life events (e.g. death in the family, divorce, etc.) (van Eck et al., 2005) (van Eck et al., 2005), through a set of items in which respondents indicate the respective level of threat it represents (T. Brugha, Bebbington, Tennant, & Hurry, 1985) (Rosmalen et al., 2012); and the Self-assessment Morningness-Eveningness **{SAME}** questionnaire by Horne et al. allows to collect information related to the respondents' circadian cycles (Horne & Ostberg, 1976).

In addition to written response questionnaires, there are also **non-verbal** response questionnaires: the Self-Assessment Manikin {SAM} (Margaret M. Bradley & Lang, 1994) is a technique for measuring a person's emotional reaction (EMOTIONS) to a given stimulus (cf. valence, arousal, and dominance dimensions), using manikins (i.e. pictures) representing emotional states (cf. happy/unhappy, excited/calm, and controlled/uncontrolled) (Herbon et al., 2005)) (Margaret M. Bradley & Lang, 1994); the name of the Circumplex Model of Affect **{CIRCUMPLEX}** given by Russell (Russell, 1980) comes from the circular pattern drawn by the structure of discrete emotions identified in the two-dimensional plane based on their degree of valence and arousal (EMOTIONS) (Herbon et al., 2005) and although it is a simple and quick model to administer, it can represent many emotional states (LiKamWa et al. used the CIRCUMPLEX concept to question the user through two input bars about the valence and arousal felt) (LiKamWa et al., 2013); the Affect Grid **{AFFECTGRID}**, created based on CIRCUMPLEX, is a scale also designed by Russell et al. to assess affect in the dimensions of the arousal/valence (AV) space (cf. pleasure/displeasure and arousal/sleepiness) in a simple and quick way (Russell, Weiss, & Mendelsohn, 1989) and is answered by placing marks in the squares of the AV

(Mandryk & Atkins, 2007) (Alzoubi et al. used the AFFECTGRID as an instrument to collect levels of perceived valence and arousal (EMOTIONS) (Alzoubi et al., 2013)).

Questionnaires used to support the screening processes were also identified in the analyzed investigations: Marlowe-Crowne Social Desirability Scale **{MCSDS}** is a questionnaire widely used to assess social desirability, i.e. the need for social approval felt by an individual. (Leite, 2005) (D P Crowne & Marlowe, 1960) (Douglas P. Crowne & Marlowe, 1960); the Affect Intensity Measure **{AIM}** was developed by Larsen (R. J. Larsen, 1984) is a questionnaire designed to measure the intensity of emotions felt to typical life events (EMOTIONS) (Larsen, 1993) (Weinfurt, Bryant, & Yarnold, 1994) (Randy J. Larsen & Diener, 1987); the Differential Emotion Scale **{DES}** is an instrument consisting of a list of adjectives to assess the subjectivity of respondents' verbal descriptions, asking respondents to rate the intensity of a word to describe a particular feeling at the time of response (EMOTIONS) (Izard E., 1972) (Boyle, 1984); the Minnesota Multiphasic Personality Inventory **{MMPI}** (later MMPI-2) assesses the respondent's personality (PERSON) and has several versions (e.g. forensic assessment, job selection, adolescents (MMPI-A), etc.) (Schiele, Baker, & Hathaway, 1943) (Buutcher et al., 2001); the Questionnaire for Mental Imagery **{QMI}** allows for the assessment of the respondents' ability to interpret images (used mainly in screening processes) (Sheehan, 1967), and the Toronto Alexithymia Scale **{TAS}** is an instrument to assess the ability to interpret emotions from images (also used in screening processes) (G. J. Taylor, Ryan, & Bagby, 1985) (Bagby, Parker, & Taylor, 1994).

RESEARCH	INSTRUMENTS & SENSORS	
	FORMAL QUESTIONNAIRES	OTHERS
Sano & Eng (Sano & Eng, 2016)	{SAME, PSQI} *(SLEEP*),* {MBTI, BFIPT} *(PERSON),* {PSS} *(STRESS*),* {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*.	**Q. informal:** {INFORMAL} *(AGE, GENDER, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*. **(T. NON-OBSTRUCTIVE)** {FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*. **(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*, {Undefined(*PSG*)*} (PSG)*, {Undefined(EOG)} *(EOG)*, {Undefined(*EMG*)*} (EMG)* and {Undefined(MELAT)} *(MELAT)*.
Zenonos et al. (Zenonos et al., 2016)	{HEALTHYOFFICE} *(MOOD*, EMOTIONS*)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {SILMEEW2X, SILMEEBTYPE} *(ECG(HR(IBI(RMSSD, SDNN)), HRV), PPG(PR, PTT), ST)*. **(OTHERS)** {HRVAS} *(HRV)* and {HAR} *(ACC)*.
Bogomolov et al. (Bogomolov et al., 2014)	{BFIPT} *(PERSON)*.	**Q. informal:** {INFORMAL} *(STRESS)*. **(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, PROXIMITY)* and {EXISTINGDATA} *(WEATHER)*.

Alzoubi et al. (Alzoubi et al., 2013)	{AFFECTGRID} *(EMOTIONS*)*.	**(T. OBSTRUCTIVE)** {MP150} *(ECG(HRV), EMG, EDA, RESP)*. **(OTHERS)** {ACQK}.
Sano & Picard (Sano & Picard, 2013b)	{PSS**} *(STRESS*)*, {PSQI**} *(SLEEP)* and {BFIPT**} *(PERSON)*.	**Q. informal:** {INFORMAL} *(SLEEP, ELECTR, HEALTH, MOOD, ALERT, TIRED, STRESS, NAP, CAFFEI, ALCOH)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ACC)* and {FUNF} *(CALL, SMS, LOCAL, SCREEN)*.
Babiker et al. (Babiker et al., 2013)	{PANES-X} *(EMOTIONS*)*.	**(T. NON-OBSTRUCTIVE)** {TX300} *(EYES, GAZE, PUPIL)*.
LikamWa et al. (LiKamWa et al., 2013)	{CIRCUMPLEX***} *(MOOD*)*. *** author's adaptation	**(T. NON-OBSTRUCTIVE)** {MOODSCOPE} *(SMS, EMAIL, CALL, APPS, BROWSER, LOCAL)*.
C. Y. Chang et al. (Chang et al., 2012)	{SAM} *(EMOTIONS*)*.	**(T. OBSTRUCTIVE)** {ML870} *(ECG, BVP, PR, EDA)*.
Y. Liu et al. (Y. Liu et al., 2010)	{SAM} *(EMOTIONS*)*.	**Q. informal:** {INFORMAL} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {EPOC} *(EEG)*. **(OTHERS)** {EPOC-SDK}.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	{SAM} *(EMOTIONS*)*.	**Q. informal:** {INFORMAL} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {HEALTHLAB} *(RESP(RR, RDEP), EDA, ECG(HR, HRV, IBI), EMG, ST)*.
Herbon et al. (Herbon et al., 2005)	{SAM} *(EMOTIONS*)*.	**Q. informal:** {INFORMAL} *(GENDER, AGE, HEALTH, TECHEXPERT)*. **(T. SLIGHTLY OBSTRUCTIVE)** {HERBON} *(PUPIL)*. **(T. OBSTRUCTIVE)** {Undefined(EDA), Undefined(ST), Undefined(HR)} *(EDA, ST, HR)*.
Van Eck et al. (van Eck et al., 2005)	{PSS**} *(STRESS*)*, {LTE} *(LIFEEVENTS),* {LDI} *(DIFFICULTIES),* {PSC} *(HEALTH),* {SDS} *(DEPRESSION)*, {STAI} *(ANXIETY)* and {STAS} *(ANGER)*.	**Q. informal:** {INFORMAL} *(MOOD, WELLBEING, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH, EMOTIONS).* **(T. OBSTRUCTIVE)** {CORTISOL, SALIVETTE} *(CORT)*.
C J Harmer et al. (C J Harmer et al., 2003)	{BFS} *(MOOD)*.	**Q. informal:** {INFORMAL} *(EMOTIONS, ENERGY, ANXIETY).* **(T. OBSTRUCTIVE)** {MANUAL} *(SEROT).* **(OTHERS)** {INTERVIEW}.
Vrijkotte et al.	{ERI} *(STRESS*)* and {POMS} *(MOOD)*.	**Q. informal:**

(Vrijkotte et al., 2000)		{INFORMAL} *(PERSON, AGE, WORKYEARS, ACADDG, PHYSI, BMI, HEIGHT, WEIGHT, WAIST, CAFFEI, ALCOH, SMOKING)*. **(T. OBSTRUCTIVE**) {S90207} *(BP(SBP, DBP))* and {VU-MAS} *(ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC)*.
Ritz et al. (Ritz et al., 2000)	{SAM} *(EMOTIONS)*, {AIM, TAS, MCSDS}**.	**Q. informal:** {INFORMAL} *(EMOTIONS)*. **(T. OBSTRUCTIVE**) {SIREGNOSTFD5} *(ROS)*, {FH3803, GMCS5} *(VT, RR)*, {FINAPRESS4} *(HR, BP(SBP, DBP))* and {Undefined(EDA)} *(EDA)*.
Rajita Sinha (Rajita Sinha, 1996)	{MMPI, QMI, TAS, BDI, STAI}** and {DES} *(EMOTIONS)*.	**Q. informal:** {INFORMAL} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {78B} *(BP(SBP, DBP))* and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} *(ECG(HR), EDA, ST, EOG, EMG)*. **(OTHERS)** {INTERVIEW}.
Scott R. Vrana (Scott R. Vrana, 1993)	{QMI}**.	**Q. informal:** {INFORMAL} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {S75-01} *(ECG(HR))*, {Undefined(*EMG*)} *(EMG)* and {S71-22} *(EDA)*.
R Rinha et al. (R Sinha et al., 1992)	{QMI, TAS}** and {DES} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {Undefined(BP)} *(BP(SBP, DBP))*, {Undefined(ICG)} *(ICG(SV, CO, PVR, PEP, LVET))*, {Undefined(ECG)} *(ECG(HR))* and {Undefined(*PCG*)} *(PCG)*. **(OTHERS)** {INTERVIEW, OBSERVATION}.

*() represents a raw signal; {} an instrument; * probably used for ground truth collection; **used in the screening process.*

3.2.2. Informal questionnaires

The need to collect specific information in the context of an investigation leads researchers to use specific questionnaires in their investigations. In this section we present questionnaires present in the research analyzed, whose validity could not be verified based on scientific evidence or reuse by other researchers. Included in this category are data collected from diaries or other types of notes requested from individuals.

Researchers use informal **(INFORMAL)** questionnaires essentially to collect information about the emotions felt (EMOTIONS): Matlovic et al. used a questionnaire with questions related to the emotions felt by participants when watching videos (e.g. "How strong was the emotion that you felt? (arousal)", "How positive was the emotion that you felt? (valence)" and "What emotion did you feel the most?") (Matlovic et al., 2016); Z. Zhang et al. asked participants in their experiment to indicate on a tablet the emotions they felt from a closed list of options (e.g. "relaxed", "surprised", "sad", "happy/amusement", etc.) and the respective intensity felt using a likert scale (Z. Zhang et al., 2016); C J Harmer et al. used visual analogue scales to collect diverse emotional information (e.g. happiness, sadness, fear, disgust, anger, etc.) (C J Harmer et al., 2003); Lisetti & Nasoz asked participants to, for each video scene viewed, indicate the emotion felt from a closed list of options (it still allowed for the manual insertion of an unanticipated emotion), the felt intensity of that emotion, and whether there was another emotion felt with relief other than the one selected (Lisetti & Nasoz, 2004); Rajita Sinha used a questionnaire to support the creation of her experience scenario where participants were asked to describe a situation in their lives that provoked the emotion felt for each image viewed (remember a situation in their lives whose emotion was equivalent to the feeling caused by the image viewed) (Rajita Sinha, 1996); and Y. Liu et al. in addition to using the SAM only to collect two domains (cf. arousal and valence), asked participants in their experiment to annotate in their own words the emotions they felt when listening to sounds from the International Affective Digitized Sounds (IADS) database (presented later in this paper) (Y. Liu et al., 2010).

However, informal questionnaires are also used by researchers to collect other data of psychosocial origin: Sano et al. used the smartphone to ask participants questions related to sleep (SLEEP), alertness level (ALERT), stress (STRESS), tiredness (TIRED), etc. (Sano & Picard, 2013b); Sano et al. after analyzing some formal questionnaires, preempted their use because of their size, opting for the use of simple scales answered through sliders [0:100] (e.g. Sad-Happy (HAPPY); Sleepy-Alert (ALERT); Sick-Healthy (HEALTH); etc.) (Sano & Eng, 2016); Hernandez et al. aiming to assess the quality of social interactions from phone calls (SOCIAL), asked participants in their experiment to respond in two seconds to the question "How was the last call?" using a seven-point likert scale representative of the stress caused (Hernandez et al., 2011); Jaques et al. used a questionnaire to collect data about the duration of curricular academic activities (ACADCL), physical exercise (PHYSI), study time (ACADST), sleep (SLEEP), naps (NAP), alcohol consumption (ALCOH), caffeine intake (CAFFEI), etc. (Jaques et al., 2015); Healey et al. used a questionnaire with questions to measure drivers' STRESS in driving-related events (J. A. Healey & Picard, 2005); and Jennifer a Healey et al. created a specific questionnaire to collect data related to the activity of driving (e.g. "How often do you usually drive?", "Do you own a car or have a car you can use frequently?", "In generak, do you feel you are more stressed than others, less stressed than others, or at about the same level as others?", etc.) (Jennifer a Healey et al., 2000).

RESEARCH	INSTRUMENTS & SENSORS	
	QUESTIONS INFORMATION	OTHERS
Matlovic et al. (Matlovic et al., 2016)	{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {FACEREADER, SHORE}. **(T. OBSTRUCTIVE)** {EPOC} *(EEG)* and {TGSR} *(EDA)*. **(OTHERS)** {TSTUDIO, CAPTIV}.
Z. Zhang et al. (Z. Zhang et al., 2016)	{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {DI3D, A655SC, VIDEO} *(HEAD, FACS, ST).* **(T. OBSTRUCTIVE)** {MP150, NIBP100D} *(BP(SBP, DBP), HR, PR, RESP(RR)) and* {Undefined(EDA)} *(EDA)*.
Sano & Eng (Sano & Eng, 2016)	{INFORMAL**} *(AGE, GENDER, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*.	**<u>Q. formal:</u>** {SAME, PSQI} *(SLEEP)*, {MBTI, BFIPT} *(PERSON)*, {PSS} *(STRESS)*, {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*. **(T. NON-OBSTRUCTIVE)** {FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*. **(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*, {Undefined(*PSG*)*} (PSG)*, {Undefined(EOG)} *(EOG)*, {Undefined(EMG)} *(EMG)* and {Undefined(MELAT)} *(MELAT)*.
Zhao et al. (Zhao et al., 2016)	{INFORMAL} *(EMOTIONS*)*.	**(T. NON-OBSTRUCTIVE)** {EQ-RADIO} *(HR(IBI(RMSSD, SDNN)), RESP) and* {VIDEO}. **(T. OBSTRUCTIVE)** {Undefined(ECG)} *(ECG(HR)).*
Jaques et al. (Jaques et al., 2015)	{INFORMAL} *(HAPPY*, ACADCL, ACADEX, ACADST, PHYSI, SOCIAL, CAFFEI, ALCOH, DRUGS, STRESS, HEALTH, ENERGY, ALERT, CALM, SLEEP, NAP)*.	**(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, SCREEN, LOCAL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ST, ACC).*
Matiko et al. (Matiko et al., 2014)	{INFORMAL} *(EMOTIONS*)*.	**(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*.
Bogomolov et al. (Bogomolov et al., 2014)	{INFORMAL} *(STRESS*)*.	**<u>Q. formal:</u>** {BFIPT} *(PERSON)*. **(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, PROXIMITY)* and {EXISTINGDATA} *(WEATHER)*.
Kusserow et al. (Kusserow et al., 2013)	{INFORMAL} *(STRESS*, MOOD)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {TALKASSIST} *(HR(HRV), EDA, ACC, ST)*, {KUSSEROW2} *(ECG(HR), ACC)*, {KUSSEROW3} *(ECG(HR), ACC)* and {KUSSEROW4} *(HR, ACC)*.
Sano & Picard (Sano & Picard, 2013b)	{INFORMAL} *(SLEEP, ELECTR, HEALTH, MOOD, ALERT, TIRED, STRESS, NAP, CAFFEI, ALCOH)*.	**<u>Q. formal:</u>** {PSS} *(STRESS)*, {PSQI} *(SLEEP)* and {BFIPT} *(PERSON)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ACC)* and {FUNF} *(CALL, SMS, LOCAL, SCREEN)*.

Kawai et al. (Kawai et al., 2013)	{INFORMAL} *(EMOTIONS*)*.	**(T. NON-OBSTRUCTIVE)** {XCEI30} *(PUPIL)*. **(OTHERS)** {DS400}.
Hernandez et al. (Hernandez et al., 2011)	{INFORMAL} *(STRESS*)*.	**(T. NON-OBSTRUCTIVE)** {EXISTINGDATA} *(CALL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
N. Lane et al. (N. Lane et al., 2011)	{INFORMAL} *(DEPRESSION, SLEEP, WELLBEING*)*.	**(T. NON-OBSTRUCTIVE)** {BEWELL} *(SLEEP, PHYSI, TALK, LOCAL, ACC)*. **(OTHERS)** {HAR}.
Y. Liu et al. (Y. Liu et al., 2010)	{INFORMAL} *(EMOTIONS)*.	**<u>Q. formal:</u>** {SAM} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {EPOC} *(EEG)*. **(OTHERS)** {EPOC-SDK}.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	{INFORMAL} *(EMOTIONS*)*.	**<u>Q. formal:</u>** {SAM} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {HEALTHLAB} *(RESP(RR, RDEP), EDA, ECG(HR, HRV, IBI), EMG, ST)*.
Mandryk & Atkins (Mandryk & Atkins, 2007)	{INFORMAL} *(EMOTIONS*)*.	**(T. NON-OBSTRUCTIVE)** {VIDEO, AUDIO}. **(T. OBSTRUCTIVE)** {PROCOMP} *(EDA, ECG(HR), EMG)*. **(OTHERS)** {BIOGRAPH}.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	{INFORMAL} *(STRESS*)*.	**(T. NON-OBSTRUCTIVE)** {VIDEO}. **(T. OBSTRUCTIVE)** {FLEXCOMP} *(ECG(HR, HRV), EMG, EDA, RESP).* **(OTHERS)** {OBSERVATION} *(STRESS)*.
Herbon et al. (Herbon et al., 2005)	{INFORMAL} *(GENDER, AGE, HEALTH, TECHEXPERT)*.	**<u>Q. formal:</u>** {SAM} *(EMOTIONS)*. **(T. SLIGHTLY OBSTRUCTIVE)** {HERBON} *(PUPIL)*. **(T. OBSTRUCTIVE)** {Undefined(EDA), Undefined(ST), Undefined(HR)} *(EDA, ST, HR)*.
Partala et al. (Partala et al., 2005)	{INFORMAL} *(EMOTIONS*).*	**(T. OBSTRUCTIVE)** {MODEL15} *(EMG)*. **(OTHERS)** {LINK15}.
Van Eck et al. (van Eck et al., 2005)	{INFORMAL} *(MOOD*, WELLBEING, PHYSI, SMOKING, FOOD, CAFFEINE, ALCOHOL, EMOTIONS*).*	**<u>Q. formal:</u>** {PSS} *(STRESS)*, {LTE} *(LIFEEVENTS),* {LDI} *(DIFFICULTIES),* {PSC} *(HEALTH),* {SDS} *(DEPRESSION)*, {STAI} *(ANXIETY)* and {STAS} *(ANGER)*. **(T. OBSTRUCTIVE)**

		{CORTISOL, SALIVETTE} *(CORT)*.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	{INFORMAL} *(AGE, GENDER, ETHNICITY, EMOTIONS)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {JAWBONE} *(EDA, HR, ST)*.
K. H. Kim et al. (K. H. Kim et al., 2004)	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {MP100} *(ECG(HR,HRV), PPG, ST, EDA)*.
Partala & Surakka (Partala & Surakka, 2003)	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {ASL4000} *(PUPIL)*. **(OTHERS)** {PSYSCOPE}.
C J Harmer et al. (C J Harmer et al., 2003)	{INFORMAL} *(EMOTIONS, ENERGY, ANXIETY)*.	**<u>Q. formal:</u>** {BFS} *(MOOD)*. **(T. OBSTRUCTIVE)** {MANUAL} *(SEROT)*. **(OTHERS)** {INTERVIEW}.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {ORION, SALIVETTE} *(CORT)* and {Undefined(EMG)} *(EMG)*.
Jennifer a Healey (Jennifer a Healey et al., 2000)	{INFORMAL} *(STRESS*)*.	**(T. OBSTRUCTIVE)** {PROCOMP} *(EDA, PPG(BVP(HR)), EMG, RESP)* and {Undefined(ECG)} *(ECG(HR, HRV))*.
Vrijkotte et al. (Vrijkotte et al., 2000)	{INFORMAL} *(PERSON, AGE, WORKYEARS, ACADDG, PHYSI, BMI, HEIGHT, WEIGHT, WAIST, CAFFEI, ALCOH, SMOKING)*.	**<u>Q. formal:</u>** {ERI} *(STRESS)* and {POMS} *(MOOD)*. **(T. OBSTRUCTIVE)** {S90207} *(BP(SBP, DBP))* and {VU-MAS} *(ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC)*.
Ritz et al. (Ritz et al., 2000)	{INFORMAL} *(EMOTIONS)*.	**<u>Q. formal:</u>** {SAM} *(EMOTIONS)*, {AIM, TAS, MCSDS}. **(T. OBSTRUCTIVE)** {SIREGNOSTFD5} *(ROS)*, {FH3803, GMCS5} *(VT, RR)*, {FINAPRESS4} *(HR, BP(SBP, DBP))* and {Undefined(EDA)} *(EDA)*.
Rajita Sinha (Rajita Sinha, 1996)	{INFORMAL} *(EMOTIONS)*.	**<u>Q. formal:</u>** {MMPI, QMI, TAS, BDI, STAI} and {DES} *(EMOTIONS)*. **(T. OBSTRUCTIVE)** {78B} *(BP(SBP, DBP))* and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} *(ECG(HR), EDA, ST, EOG, EMG)*. **(OTHERS)** {INTERVIEW}.
Scott R. Vrana (Scott R. Vrana, 1993)	{INFORMAL} *(EMOTIONS)*.	**<u>Q. formal:</u>** {QMI}. **(T. OBSTRUCTIVE)** {S75-01} *(ECG(HR))*, {Undefined(*EMG*)} *(EMG)* and {S71-22} *(EDA)*.

*() represents a raw signal; {} an instrument; * probably used for ground truth collection; **used in the screening process.*

3.2.3. Analysis

Psychologists commonly use questionnaires to gauge emotional states. These instruments are considered valid by the literature and are widely used by the medical and scientific community. However, questionnaires are not suitable instruments for collecting volatile information because of the constant confrontation of people with different stimuli potentially generating emotional changes (Matlovic et al., 2016). In addition they are not immune to the problems of subjectivity and influences that may arise from the context (Johnston et al., 2009) (R. J. Pagulayan, Keeker, Wixon, Romero, & Fuller, 2012). But in addition to subjectivity, questionnaires have other problems: they do not account for individual respondent characteristics because they do not consider that people perceive emotions differently from one another (Zenonos et al., 2016) (Raudonis, 2013) (Canini et al., 2009) (Bago d'Uva, Van Doorslaer, Lindeboom, & O'Donnell, 2008); measure deferred and scalar in time (Tran et al., 2007); the mere presence of the inquirers may cause the sense of less severity and greater emotional balance (Wikia, n.d.); etc.

Researchers tend to distrust questionnaires (Tran et al., 2007) (Bound, 1991). In addition to being subjective measurement techniques, they are limited because they do not allow for real-time data capture. Because they involve interrupting tasks in order for data collection to happen, they can be considered disruptive techniques that add noise and subtract quality from the data collected (Tran et al., 2007) (Mandryk & Atkins, 2007) as data can be corrupted as a result of interrupting the stimulus whose reaction it was intended to measure (experiments conducted by Mandryk et al. showed that the act of filling out a questionnaire or communicating with the inquirer, caused a change in physiological signals in the participants of their experiment (Mandryk & Atkins, 2007)). However, although there is little evidence that data from questionnaires are meaningful, there are many researchers who use them (Oswald & Wu, 2010) because they allow us to understand users' attitudes and behaviors (R. Pagulayan et al., 2012).

There are many formal questionnaires used by researchers, either in screening processes or in collecting context data. The great advantage of using formal questionnaires in research is their acceptance by the scientific community because they are instruments recognized in the literature. The different tests and various reuses in different investigations and contexts confer validity to the method and the data collected by it. However, the investigations analyzed in this survey do not clarify the use of versions benchmarked to the population represented in the sample used in the experiments, raising questions regarding the validity of the data collected. For example, the answers given to a questionnaire to collect health status (HEALTH) (e.g. SF-12), can be influenced by several factors: individual concept of health; available healthcare system; education; socioeconomic conditions; monthly income; understanding of the questionnaire questions; etc. As all these factors may vary depending on the geographic location, it makes sense to cater for demographic specificities by using questionnaires (or versions of questionnaires) tailored for each population (Bago d'Uva et al., 2008) (Johnston et al., 2009).

Researchers also resort to using informal questionnaires to collect data for use in their systems. Perhaps the high number of investigations that use this technique is justified by the need to obtain specific data not foreseen by formal questionnaires, or by the fact that these are more time consuming to complete or are not fully framed in the researchers' objectives. The great advantage of using informal questionnaires is the freedom in adapting the instrument to the research, being possible to directly collect the desired subjective measure. However, the absence of evidence to support the quality of the instrument, such as pre-testing, calls into question the validity of the data collected and, consequently, of the results obtained by the systems.

RESEARCH	FORMAL QUESTIONNAIRES	INFORMAL QUESTIONNAIRES	OTHER
Matlovic et al. (Matlovic et al., 2016)		{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {FACEREADER, SHORE}. **(T. OBSTRUCTIVE)** {EPOC} *(EEG)* and {TGSR} *(EDA)*. **(OTHERS)** {TSTUDIO, CAPTIV}.
Z. Zhang et al. (Z. Zhang et al., 2016)		{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {DI3D, A655SC, VIDEO} *(HEAD, FACS, ST).* **(T. OBSTRUCTIVE)** {MP150, NIBP100D} *(BP(SBP, DBP), HR, PR, RESP(RR)) and* {Undefined(EDA)} *(EDA)*.
Sano & Eng (Sano & Eng, 2016)	{SAME, PSQI} *(SLEEP),* {MBTI, BFIPT} *(PERSON),* {PSS} *(STRESS),* {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*.	{INFORMAL} *(AGE, GENDER, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*.	**(T. NON-OBSTRUCTIVE)** {FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*. **(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*, {Undefined(PSG)} *(PSG)*, {Undefined(EOG)} *(EOG)*, {Undefined(EMG)} *(EMG)* and {Undefined(MELAT)} *(MELAT)*.
Zhao et al. (Zhao et al., 2016)		{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {EQ-RADIO} *(HR(IBI(RMSSD, SDNN)), RESP) and* {VIDEO}. **(T. OBSTRUCTIVE)** {Undefined(ECG)} *(ECG(HR)).*
Zenonos et al. (Zenonos et al., 2016)	{HEALTHYOFFICE} *(MOOD, EMOTIONS)*.		**(T. SLIGHTLY OBSTRUCTIVE)** {SILMEEW2X, SILMEEBTYPE} *(ECG(HR(IBI(RMSSD, SDNN)), HRV), PPG(PR, PTT), ST)*. **(OTHERS)** {HRVAS} *(HRV)* and {HAR} *(ACC)*.
Jaques et al. (Jaques et al., 2015)		{INFORMAL} *(HAPPY, ACADCL, ACADEX, ACADST, PHYSI, SOCIAL, CAFFEI, ALCOH, DRUGS, STRESS,*	**(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, SCREEN, LOCAL)*. **(T. SLIGHTLY OBSTRUCTIVE)**

		HEALTH, ENERGY, ALERT, CALM, SLEEP, NAP).	{AFFECTIVAQ} *(EDA, ST, ACC)*.
Matiko et al. (Matiko et al., 2014)		{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*.
Bogomolov et al. (Bogomolov et al., 2014)	{BFIPT} *(PERSON)*.	{INFORMAL} *(STRESS)*.	**(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, PROXIMITY)* and {EXISTINGDATA} *(WEATHER)*.
Kusserow et al. (Kusserow et al., 2013)		{INFORMAL} *(STRESS, MOOD)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {TALKASSIST} *(HR(HRV), EDA, ACC, ST)*, {KUSSEROW2} *(ECG(HR), ACC)*, {KUSSEROW3} *(ECG(HR), ACC)* and {KUSSEROW4} *(HR, ACC)*.
Alzoubi et al. (Alzoubi et al., 2013)	{AFFECTGRID} *(EMOTIONS)*.		**(T. OBSTRUCTIVE)** {MP150} *(ECG(HRV), EMG, EDA, RESP)*. **(OTHERS)** {ACQK}.
Sano & Picard (Sano & Picard, 2013b)	{PSS} *(STRESS)*, {PSQI} *(SLEEP)* and {BFIPT} *(PERSON)*.	{INFORMAL} *(SLEEP, ELECTR, HEALTH, MOOD, ALERT, TIRED, STRESS, NAP, CAFFEI, ALCOH)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ACC)* and {FUNF} *(CALL, SMS, LOCAL, SCREEN)*.
Kawai et al. (Kawai et al., 2013)		{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {XCEI30} *(PUPIL)*. **(OTHERS)** {DS400}.
Babiker et al. (Babiker et al., 2013)	{PANES-X} *(EMOTIONS)*.		**(T. NON-OBSTRUCTIVE)** {TX300} *(EYES, GAZE, PUPIL)*.
LikamWa et al. (LiKamWa et al., 2013)	{CIRCUMPLEX} *(MOOD)*.		**(T. NON-OBSTRUCTIVE)** {MOODSCOPE} *(SMS, EMAIL, CALL, APPS, BROWSER, LOCAL)*.
C. Y. Chang et al. (Chang et al., 2012)	{SAM} *(EMOTIONS)*.		**(T. OBSTRUCTIVE)** {ML870} *(ECG, BVP, PR, EDA)*.
Hernandez et al. (Hernandez et al., 2011)		{INFORMAL} *(STRESS)*.	**(T. NON-OBSTRUCTIVE)** {EXISTINGDATA} *(CALL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
N. Lane et al. (N. Lane et al., 2011)		{INFORMAL} *(DEPRESSION, SLEEP, WELLBEING)*.	**(T. NON-OBSTRUCTIVE)** {BEWELL} *(SLEEP, PHYSI, TALK, LOCAL, ACC)*. **(OTHERS)** HAR}.

Y. Liu et al. (Y. Liu et al., 2010)	{SAM} *(EMOTIONS)*.	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {EPOC} *(EEG)*. **(OTHERS)** {EPOC-SDK}.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	{SAM} *(EMOTIONS)*.	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {HEALTHLAB} *(RESP(RR, RDEP), EDA, ECG(HR, HRV, IBI), EMG, ST)*.
Mandryk & Atkins (Mandryk & Atkins, 2007)		{INFORMAL} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {VIDEO, AUDIO}. **(T. OBSTRUCTIVE)** {PROCOMP} *(EDA, ECG(HR), EMG)*. **(OTHERS)** {BIOGRAPH}.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)		{INFORMAL} *(STRESS)*.	**(T. NON-OBSTRUCTIVE)** {VIDEO}. **(T. OBSTRUCTIVE)** {FLEXCOMP} *(ECG(HR, HRV), EMG, EDA, RESP)*. **(OTHERS)** {OBSERVATION} *(STRESS)*.
Herbon et al. (Herbon et al., 2005)	{SAM} *(EMOTIONS)*.	{INFORMAL} *(GENDER, AGE, HEALTH, TECHEXPERT)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {HERBON} *(PUPIL)*. **(T. OBSTRUCTIVE)** {Undefined(EDA), Undefined(ST), Undefined(HR)} *(EDA, ST, HR)*.
Partala et al. (Partala et al., 2005)		{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {MODEL15} *(EMG)*. **(OTHERS)** {LINK15}.
Van Eck et al. (van Eck et al., 2005)	{PSS} *(STRESS)*, {LTE} *(LIFEEVENTS)*, {LDI} *(DIFFICULTIES)*, {PSC} *(HEALTH)*, {SDS} *(DEPRESSION)*, {STAI} *(ANXIETY)* and {STAS} *(ANGER)*.	{INFORMAL} *(MOOD, WELLBEING, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH, EMOTIONS)*.	**(T. OBSTRUCTIVE)** {CORTISOL, SALIVETTE} *(CORT)*.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		{INFORMAL} *(AGE, GENDER, ETHNICITY, EMOTIONS)*.	**(T. SLIGHTLY OBSTRUCTIVE)** {JAWBONE} *(EDA, HR, ST)*.
K. H. Kim et al. (K. H. Kim et al., 2004)		{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {MP100} *(ECG(HR,HRV), PPG, ST, EDA)*.
Partala & Surakka (Partala & Surakka, 2003)		{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {ASL4000} *(PUPIL)*. **(OTHERS)** {PSYSCOPE}.
C J Harmer et al. (C J Harmer et al., 2003)	{BFS} *(MOOD)*.	{INFORMAL} *(EMOTIONS, ENERGY, ANXIETY)*.	**(T. OBSTRUCTIVE)** {MANUAL} *(SEROT)*. **(OTHERS)**

			{INTERVIEW}.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)		{INFORMAL} *(EMOTIONS).*	**(T. OBSTRUCTIVE)** {ORION, SALIVETTE} *(CORT)* and {Undefined(EMG)} *(EMG)*.
Jennifer a Healey (Jennifer a Healey et al., 2000)		{INFORMAL} *(STRESS).*	**(T. OBSTRUCTIVE**) {PROCOMP} *(EDA, PPG(BVP(HR)), EMG, RESP)* and {Undefined(*ECG*)} *(ECG(HR, HRV))*.
Vrijkotte et al. (Vrijkotte et al., 2000)	{ERI} *(STRESS)* and {POMS} *(MOOD)*.	{INFORMAL} *(PERSON, AGE, WORKYEARS, ACADDG, PHYSI, BMI, HEIGHT, WEIGHT, WAIST, CAFFEI, ALCOH, SMOKING)*.	**(T. OBSTRUCTIVE**) {S90207} *(BP(SBP, DBP))* and {VU-MAS} *(ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC)*.
Ritz et al. (Ritz et al., 2000)	{SAM} *(EMOTIONS)*, {AIM, TAS, MCSDS}.	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE**) {SIREGNOSTFD5} *(ROS)*, {FH3803, GMCS5} *(VT, RR)*, {FINAPRESS4} *(HR, BP(SBP, DBP))* and {Undefined(EDA)} *(EDA)*.
Rajita Sinha (Rajita Sinha, 1996)	{MMPI, QMI, TAS, BDI, STAI} and {DES} *(EMOTIONS)*.	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {78B} *(BP(SBP, DBP))* and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} *(ECG(HR), EDA, ST, EOG, EMG)*. **(OTHERS)** {INTERVIEW}.
Scott R. Vrana (Scott R. Vrana, 1993)	{QMI}.	{INFORMAL} *(EMOTIONS)*.	**(T. OBSTRUCTIVE)** {S75-01} *(ECG(HR))*, {Undefined(EMG)} *(EMG)* and {S71-22} *(EDA)*.
R Rinha et al. (R Sinha et al., 1992)	{QMI, TAS} and {DES} *(EMOTIONS)*.		**(T. OBSTRUCTIVE)** {Undefined(BP)} *(BP(SBP, DBP))*, {Undefined(ICG)} *(ICG(SV, CO, PVR, PEP, LVET))*, {Undefined(ECG)} *(ECG(HR))* and {Undefined(*PCG*)} *(PCG)*. **(OTHERS)** {INTERVIEW, OBSERVATION}.

() represents a raw signal; and {} an instrument.

3.3. OTHER INSTRUMENTS

This section presents other instruments referenced by the analyzed literature, not included in the sections already presented. Despite their importance in emotional detection systems, they participate only indirectly in the context data collection process.

In the literature reviewed we identified the following instruments used in a secondary way in the context introspection process: the Hitachi MS-DS400 **{DS400}** recorder used by Kawai et al. to store the video collected in DVV (Kawai et al., 2013); the Tobii Studio **{TSTUDIO}** is an application used in investigations using ocular context data, supports the investigation from recording, analysis and presentation of results, and allows the presentation of questionnaires (Tobii Technology AB, 2015) (Matlovic et al., 2016); ADInstruments' LabChart application **{LABCHART}** is used as a data acquisition tool, and allows real-time and simultaneous storage and monitoring of data collected by collection sensors (e.g. ML870, FE116, ML309, ML135, etc.) (ADInstruments, n.d.-e) (there are several researchers who have used ADInstruments' systems namely LABCHART: Basu et al. (Basu et al., 2016); Mokhayeri et al. (Mokhayeri & Toosizadeh, 2011); Chang et al. (Chang et al., 2012); Ding et al. (Ding et al., 2013); etc.); the AcqKnowledge application **{ACQK}** handles information from instruments such as the MP100, MP150, and MP160 (Biopac Systems Inc, 2017c) (Biopac Systems Inc, 2017e) (Toruzyme, 2001); Captiv **{CAPTIV}** is a tool from TEA that facilitates the process of recording, synchronizing and analyzing video recordings and other collection sensors (TEA, 2016); the **MATLAB** (The Mathworks Inc., 2016) is a data analysis platform that contains several tools, and is widely used by researchers; Zenonos et al, used Ramshur's MATLAB HRVAS toolbox **{HRVAS}** for HRV extraction (Ramshur, 2010) (Zenonos et al, 2016); algorithms related to Human Activity Recognition {HAR} (Bulling, Blanke, & Schiele, 2014) (Hammerla, Kirkham, Andras, & Ploetz, 2013); Yang et al. used Emotion Avatar Images **{EAI}** in their data collection, to create generic representations of faces collected by video with the goal of diminishing person-specific features (S. Yang & Bhanu, 2011); the BioExplorer **{BIOEXPLORER** } is a software used for neurofeedback and biofeedback (e.g. Bos used it in conjunction with BQPET to collect EEG (Bos, 2010)) (Brainquiry, 2017); the Infiniti BioGraph **{BIOGRAPH}** by Thoutht Technology is used in conjunction physiological signal collection instruments and allows data visualization in graphical form during the process of raw data collection and analysis (e.g. Mandryk & Atkings used BIOGRAPH in conjunction with PROCOMP in the process of physiological signal collection (Mandryk & Atkins, 2007)) (Thought Technology Ltd., n.d.) (Thought Technology Ltd., 2016b); and Grass Link15 **{LINK15}**, used by (Partala et al., 2005), is software that assists in recording data from devices such as MODEL15.

Also in the same group of tools are the Software Development Kits (SDK) available for each product to enable integration with the devices: MINDWAVE **{MINDWAVE-SDK}** (NeuroSky, 2017); KINECT **{KINECT-SDK}** (Microsoft, 2017a); and EPOC-SDK **{EPOC-SDK}** (Emotiv, 2017).

There are also tools to support the experimental process in the context data collection phase: PsyScope **{PSYSCOPE}** is a tool used in experimental control in psychology laboratories, and allows to design and control experimental processes without programming needs (J. Cohen, MacWhinney, Flatt, & Provost, 1993) (Bonatti, 2006) (the sound stimulus administration phase of Partala et al.'s experiment was controlled by PSYSCOPE, as was the data collection process of the participants' responses (Partala & Surakka, 2003)).

Other rather residual instruments were also identified: Rajita Sinha did **{INTERVIEW}** interviews with subjects eligible to participate in her experimental process in order to administer various screening questionnaires (Rajita Sinha, 1996); Hsu et al. used INTERVIEW and behavioral observation **{OBSERVATION}** to identify emotional changes in research in which they presented the game Emotion Labyrinth (Hsu et al., 2012); and Z. Zhang et al. used INTERVIEW done by a professional actor to elicit emotions in participants through interpersonal conversation (Z. Zhang et al., 2016). Soleymani et al. used OBSERVATION to have five annotators assign a valence value to serve as ground truth to the research (Soleymani et al., 2013).

The following table summarizes the research analyzed where the instruments listed in this section were found.

RESEARCH	COLLECTION INSTRUMENTS & SENSORS	
	OTHERS	PREVIOUS
Matlovic et al. (Matlovic et al., 2016)	{TSTUDIO, CAPTIV}.	**(T. NON-OBSTRUCTIVE)** {FACEREADER, SHORE}. **(T. OBSTRUCTIVE)** {EPOC} *(EEG)* and {TGSR} *(EDA)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Gogia et al. (Gogia et al., 2016)	{MINDWAVE-SDK, KINECT-SDK}.	**(T. NON-OBSTRUCTIVE)** {KINECT, VIDEO} *(HEAD)*. **(T. SLIGHTLY OBSTRUCTIVE)** {MINDWAVE} *(EEG)*.
Zenonos et al. (Zenonos et al., 2016)	{HRVAS} *(HRV)**** and {HAR} *(ACC)*. *** HRV obtained through HRVAS.	**(T. SLIGHTLY OBSTRUCTIVE)** {SILMEEW2X, SILMEEBTYPE} *(ECG(HR(IBI(RMSSD, SDNN)), HRV***), PPG(PR, PTT), ST)*. **(Q. FORMAIS)** {HEALTHYOFFICE} *(MOOD, EMOTIONS)*.
Basu et al. (Basu et al., 2016)	{LABCHART}.	**(T. SLIGHTLY OBSTRUCTIVE)** {BIOHARNESS} *(ECG, HR, PR, RESP(RR))*. **(T. OBSTRUCTIVE)** {ML870, FE116, ML135, ML309} *(EDA, ST)* and {Undefined(EMG)} *(EMG)*.
Saha et al. (Saha et al., 2014)	{KINECT-SDK}.	**(T. NON-OBSTRUCTIVE)** {KINECT} *(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN, ACC).*
Soleymani et al. (Soleymani et al., 2013)	{OBSERVATION} *(EMOTIONS)*.	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH)*. **(T. OBSTRUCTIVE)** {ACTIVEII} *(EEG)*.
Alzoubi et al. (Alzoubi et al., 2013)	{ACQK}.	**(T. OBSTRUCTIVE)** {MP150} *(ECG(HRV), EMG, EDA, RESP)*. **(Q. FORMAIS)** {AFFECTGRID} *(EMOTIONS)*.
Kawai et al. (Kawai et al., 2013)	{DS400}.	**(T. NON-OBSTRUCTIVE)** {XCEI30} *(PUPIL)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Yang & Bhanu (S. Yang & Bhanu, 2011)	{EAI}.	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(HEAD, FACE)*.
N. Lane et al. (N. Lane et al., 2011)	{HAR}.	**(T. NON-OBSTRUCTIVE)** {BEWELL} *(SLEEP, PHYSI, TALK, LOCAL, ACC)*. **(Q. INFORMAL)** {INFORMAL} *(DEPRESSION, SLEEP, WELLBEING)*.

Bos (Bos, 2010)	{BIOEXPLORER}.	**(T. SLIGHTLY OBSTRUCTIVE)** {BQPET} *(EEG)*.
Y. Liu et al. (Y. Liu et al., 2010)	{EPOC-SDK}.	**(T. OBSTRUCTIVE)** {EPOC} *(EEG)*. **(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
Mandryk & Atkins (Mandryk & Atkins, 2007)	{BIOGRAPH}.	**(T. NON-OBSTRUCTIVE)** {VIDEO, AUDIO}. **(T. OBSTRUCTIVE)** {PROCOMP} *(EDA, ECG(HR), EMG)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	{OBSERVATION} *(STRESS*)*.	**(T. NON-OBSTRUCTIVE)** {VIDEO}. **(T. OBSTRUCTIVE)** {FLEXCOMP} *(ECG(HR, HRV), EMG, EDA, RESP).* **(Q. INFORMAL)** {INFORMAL} *(STRESS)*.
Partala et al. (Partala et al., 2005)	{LINK15}.	**(T. OBSTRUCTIVE)** {MODEL15} *(EMG)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*
Partala & Surakka (Partala & Surakka, 2003)	{PSYSCOPE}.	**(T. OBSTRUCTIVE)** {ASL4000} *(PUPIL)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*
C J Harmer et al. (C J Harmer et al., 2003)	{INTERVIEW**}.	**(T. OBSTRUCTIVE)** {MANUAL} *(SEROT)*. **(Q. FORMAIS)** {BFS} *(MOOD)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS, ENERGY, ANXIETY).*
Rajita Sinha (Rajita Sinha, 1996)	{INTERVIEW}.	**(T. OBSTRUCTIVE)** {78B} *(BP(SBP, DBP))* and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} *(ECG(HR), EDA, ST, EOG, EMG)*. **(Q. FORMAIS)** {MMPI, QMI, TAS, BDI, STAI} and {DES} *(EMOTIONS)*. **{Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.
R Rinha et al. (R Sinha et al., 1992)	{INTERVIEW, OBSERVATION}.	**(T. OBSTRUCTIVE)** {Undefined(BP)} *(BP(SBP, DBP))*, {Undefined(ICG)} *(ICG(SV, CO, PVR, PEP, LVET))*, {Undefined(ECG)} *(ECG(HR))* and {Undefined(*PCG*)} *(PCG)*. **(Q. FORMAIS)** {QMI, TAS} and {DES} *(EMOTIONS)*.

*() represents a raw signal; {} an instrument; * probably used for ground truth collection; **used in the screening process.*

3.4. ANALYSIS

The following table summarizes the instruments and sensors identified in the investigations reviewed in this literature survey.

The need to diversify the context data to be correlated makes it inevitable to use a larger number of instruments and sensors in the context introspection. However, there are several concerns to be taken into account when selecting devices: obstructiveness felt by users; quality of the data collected considering that the act of measuring may influence the data itself; price of the devices, sensors or questionnaires; choice of questionnaires suitable for the target population; ethical and security issues; etc.

The selection of instruments to be used in the creation of an automatic emotion detection system can be a challenge. Although the use of state-of-the-art technology is recommended in order to promote accuracy, performance, and low obstructivity, the budgetary constraints and expertises required to handle each instrument cannot be ignored (Caballe, 2015). VIDEO and AUDIO-based nonobstructive techniques allow for quality context data collection because of user obliviousness (Ouwerkerk et al., 2008). However, in addition to the aforementioned problems related to expression and posture, ethical and legal issues require that people be warned in advance of sound and image capture, removing the effect of people's obliviousness from the collection process. Since physiological signals are involuntary and tend to represent objective points of context data (Rani & Sarkar, 2006) should preferably be selected for correlation in the systems. However, most of the instruments available for collection are obstructive and tend to alter the habits of the users and can adulterate the data they collect. The smartphone is an instrument that, without additional user effort and without the need to add sensors, naturally provides social context data (e.g. CALL, SMS, EMAIL, etc.). In addition they collect information resulting from spontaneous behavior (Rachuri et al., 2010). However, besides the ethical issues related to privacy, there is no consensus about the best way to assess social support (J. L. Pais-Ribeiro, 1999) and is not possible to map the data collected directly onto emotions. Questionnaires are widely used in emotional assessment (Fulton & Medlock, 2003) (Mandryk & Atkins, 2007) and collect direct information of what is intended to be measured. However, despite being accepted in the literature as a way to measure emotions (Babiker et al., 2013), they represent a subjective collection technique whose responses can lead to erroneous measurements (Caballe, 2015).

In the absence of ideal forms of objective measurement, it remains to manage and mitigate the problems of existing devices. As the main purpose of the instruments and sensors is to collect quality data preferably related to the spontaneous behavior of users, it is suggested to prefer techniques with low or zero obstructivity. The use of an application to collect social context data from the smartphone (e.g. FUNF) seems essential. SILMEEW2X, SILMEEBTYPE, BQPET, JAWBONE, BIOHARNESS, MIBAND, and EDAMOVE are low obstructive and technologically up-to-date instruments. They allow collecting several physiological context variables potentially interesting for an emotional inference system (cf. number of steps, distances traveled, information about sleep, ST, ECG, PPG, BP, EDA, RESP, etc.) (Linder, 2015) (Toshiba, 2015) (Brainquiry, n.d.) (Branquiry, 2017) (Jawbone, 2017) (Medtronic, 2015) (Zephyr Technology, 2012) (XiaoMi, n.d.) (movisens GmbH, 2018b). In addition to these other current devices not referenced in the literature under review can be used: such as the Zephyr HxM for measuring HRV and RR (Medtronic, 2015); the Wahoo TICKR (Wahoo Fitness, 2018) or 4iiii Viiiiva (4iiii Innovations Inc., 2018) in conjunction with the CardioMood application for HR measurements (Expert tools for Heart Rate analysis, 2016); empatica's embrace wristband (Empatica Inc., 2017); the EdaMove 3 from movisens (movisens GmbH, 2018a); or the Oximeter from MindMedia for measuring O2 saturation in the blood (Mind Media, n.d.). In case there is no low obstructivity solution for data collection, it is suggested to use current technology sensors produced with miniaturization goals in order to have the lowest possible degree of obstructivity (e.g. products from Shimmer (Shimmer Discovery in Motion, 2017) Neurosky (Neurosky, 2017), Plux (plux, n.d.), etc.). Besides these instruments, it is also suggested to reuse existing systems to collect context data: MoodScope can contribute information about MOOD, thus avoiding the use of a questionnaire (it allows integration through its API) (LiKamWa et al., 2013); can be used Cognitive-Services from Microsoft, Emotion as a Service from Affectiva, or FACEREADER from Noldus can be used to collect emotional information (EMOTIONS) based on analysis of facial expression, speech, and body posture from VIDEO (Microsoft, 2017b) (Affectiva Inc., 2017) (Noldus, 2017); etc. In addition to these instruments, specific instruments could also be created, either by assembling sensors on platforms such as Arduino or Raspberry (Arduino, 2018) (Raspberry Pi Foundation, n.d.) or develop specific applications to extract user behavior (e.g. activity log in operating systems, screen on&off, duration and type of callers in CALL and SMS, etc.).

Despite the reservations raised, questionnaires can be important tools for an emotional recognition system because they make it easier to collect direct information of what is intended to be measured (Caballe, 2015) (Sano & Eng, 2016) (Johnston et al., 2009). Questionnaires are widely used by behavioral science researchers (Kusserow et al., 2013) and are used by health professionals in emotional assessment (Fulton & Medlock, 2003) (Mandryk & Atkins, 2007) as they are accepted instruments for this purpose (Babiker et al., 2013). However, there are several authors who avoid collecting data through questionnaires. For example, some researchers have chosen to use questionnaires for ground-truth collection in preference to multimedia resources pre-labeled by the authors with the emotions they elicit (e.g. IADS and IAPS). However, the strategy of inducing emotions with resources pre-labeled with the emotional content is also not without problems. People perceive images and sounds differently from one another, because perception depends on one's past experience and personality, and the way to weigh this information against the results of induction is precisely through individual data collection with the questionnaires that were intended to be avoided.

How questionnaires contribute important information to emotional detection systems (Bos, 2010) (Babiker et al., 2013), their use becomes unavoidable. However, the authors believe it is important to choose questionnaires benchmarked to the target population of the experiment in order to promote the quality of the collected data and decrease doubts about the validity of the obvious results. Besides the questionnaires used in the reported investigations, there are others that can contribute interesting contextual data to an emotional detection system: the Social Readjustment Rating Scale (SRRS) by Holmes and Rahe (Holmes & Rahe, 1967) designed to identify the most stressful life events of the past 12 months by assigning each event a traumatic weight based on the respondent's feelings (McLeod, 2010); the *Escala de Satisfação com o Suporte Social de Pais Ribeiro* (ESSS) which assesses satisfaction with social support received (e.g., with friends, family, intimacy, and social activities) (J. L. Pais-Ribeiro, 1999). The Marlowe-Crowne Social Desirability Scale (MCSDS) and the Balanced Inventory of Desirable Responding (BIDR) are instruments that assess social desirability and the need for social approval (D P Crowne & Marlowe, 1960) (Douglas P. Crowne & Marlowe, 1960) (Leite, 2005) and can provide data of social nature; the Dyadic Adjustment Scale (R-DAS) that assesses satisfaction, cohesion and consensus among spouses (Portuguese version (Pereira, 2003)) (Spanier, 1976); the Rosenberg Self-Esteem Scale (RSES) is one of the oldest scales for the global assessment of self-esteem in adolescents, (i.e. positive self-concept, social acceptance, self-efficacy, and life satisfaction) (Santos et al. presented a preliminary version for the Portuguese population

(Santos & Maia, 2003) and Pechorro et al. performed a validation for Portuguese adolescents in a forensic context (Pechorro, Marôco, Poiares, & Vieira, 2011)) (Baumeister et al., 2013) (Rosenberg, 1965) may contribute data about self-esteem; the World Health Organization Quality-Of-Life assessment (WHOQOLBREF) is the WHO short questionnaire for measuring quality of life (Group, 1998) (Rehabilitation Institute of Chicago, 2014) (Vaz Serra et al., 2006) (Universidade de Coimbra, n.d.) and can collect information about people's quality of life; the 21-item Anxiety, Depression and Stress Scale (EADS-21) (Portuguese adaptation) can measure ANXIETY, DEPRESSION and STRESS in a tripartite way (J. Pais-Ribeiro et al., 2007); the Oxford Happiness Questionnaire (OHQ) is a questionnaire widely used by researchers to measure happiness (HAPPY) and is used in the assessment of subjective well-being (Hills & Argyle, 2002); the Patient Health Questionnaire (PHQ-9), created by Kroenke for the assessment of depression, is one of the most widely used questionnaires for mental health assessment and is composed of nine diagnostic items (cf. anhedonia (i.e., lack of feelings of pleasure), depressed mood, difficulty sleeping, feeling tired, change in appetite, feelings of guilt or worthlessness, difficulty concentrating, lack of rhythm or restlessness, and suicidal thoughts) (Kroenke, Spitzer, & Williams, 2001) (Sano & Eng, 2016); the Goldberg Anxiety and Depression Scale (GADS) is an eighteen-item questionnaire to assess depression and anxiety experienced in the past month (nine for anxiety and nine for depression), designed to be administered by non-medical personnel (Goldberg, Bridges, Duncan-Jones, & Grayson, 1988); the Spiritual Well-Being Questionnaire (SWBQ) that evaluates the spiritual well-being (Gouveia & Marques, 2005). (Gouveia & Marques, 2009); *Échelle de Mesure des Manifestations du Bien-Être Psychologique* (EMMBEP) (Portuguese version) (Monteiro, Tavares, Pereira, & Universidade de Aveiro, 2012); Satisfaction With Life Scale (SWLS) (Diener, Emmons, Larsen, & Griffin, 1985) validated for Portuguese by Simões (ESV) (Simões, 1992); social Well-Being Questionnaire that aims to measure the well-being of people from a social perspective (Radzyk, 2014); Well-Being Questionnaire (W-BQ12) (Portuguese version) (P. C. Bradley & Holloway, n.d.) (Koch, 2012); and the Product Emotion Measurement Instrument (PrEmo) (PREMO) which is a picture response questionnaire and measures seven positive and seven negative emotions (EMOTIONS) (most commonly used to assess the emotional impact of products) (Wassink, 2013) (P. M. to Desmet, 2005) can be used to measure EMOTIONS. Informal specific questionnaires may also be used. However, they will be applied only after the necessary pre-tests, and the questions will preferably be inspired by other questionnaires adapted for the Portuguese population (e.g. collecting socio-cultural information, collecting labor data, collecting quality of sleep, fatigue, well-being, etc.).

RESEARCH	OBJECTIVE MEASUREMENT	SUBJECTIVE MEASUREMENT	OTHER INST.
Perdiz et al. (Perdiz et al., 2017)	**(T. SLIGHTLY OBSTRUCTIVE)** {IMU} *(HEAD)*. **(T. OBSTRUCTIVE)** {Undefined(EMG), Undefined(EOG)} *(EMG, EOG)*.		
S. H. Lee et al. (S. H. Lee et al., 2016)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, NOSE, LIPS, CHEEKS, JAW, MOUTH)*.		
Eckert et al. (Eckert et al., 2016)	**(T. NON-OBSTRUCTIVE)** {APP, PICTURES} *(FACS, CAUL, EYES, EYEBROWS, NOSE, MOUTH)*.		

Matlovic et al. (Matlovic et al., 2016)	**(T. NON-OBSTRUCTIVE)** {FACEREADER, SHORE}. **(T. OBSTRUCTIVE)** {EPOC} *(EEG)* and {TGSR} *(EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	{TSTUDIO, CAPTIV}.
Gogia et al. (Gogia et al., 2016)	**(T. NON-OBSTRUCTIVE)** {KINECT, VIDEO} *(HEAD)*. **(T. SLIGHTLY OBSTRUCTIVE)** {MINDWAVE} *(EEG)*.		{MINDWAVE-SDK, KINECT-SDK}.
Z. Zhang et al. (Z. Zhang et al., 2016)	**(T. NON-OBSTRUCTIVE)** {DI3D, A655SC, VIDEO} *(HEAD, FACS, ST).* **(T. OBSTRUCTIVE)** {MP150, NIBP100D} *(BP(SBP, DBP), HR, PR, RESP(RR)) and* {Undefined(EDA)} *(EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	
Sano & Eng (Sano & Eng, 2016)	**(T. NON-OBSTRUCTIVE)** {FUNF, APP} *(LOCAL, CALL, SMS, SCREEN, APPS, EMAIL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ST, ACC)* and {MOTIONLOGGER} *(ACC, LIGHT)*. **(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*, {Undefined(PSG)} *(PSG)*, {Undefined(EOG)} *(EOG)*, {Undefined(EMG)} *(EMG)* and {Undefined(MELAT)} *(MELAT)*.	**(Q. FORMAIS)** {SAME, PSQI} *(SLEEP)*, {MBTI, BFIPT} *(PERSON)*, {PSS} *(STRESS)*, {SF-12} *(HEALTH, CALM, ENERGY, MOOD)* and {STAI} *(ANXIETY)*. **(Q. INFORMAL)** {INFORMAL} *(AGE, GENDER, ACADDG, LIVING, ETHNICITY, RACE, SCHOOLY, SCHOOLA, HEALTH, SLEEP, NAP, PHYSI, ACADCL, ACADGR, ACADEX, CAFFEI, ALCOH, DRUGS, SOCIAL, HAPPY, ALERT)*.	
Zhao et al. (Zhao et al., 2016)	**(T. NON-OBSTRUCTIVE)** {EQ-RADIO} *(HR(IBI(RMSSD, SDNN)), RESP) and* {VIDEO}. **(T. OBSTRUCTIVE)** {Undefined(ECG)} *(ECG(HR)).*	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	
Zenonos et al. (Zenonos et al., 2016)	**(T. SLIGHTLY OBSTRUCTIVE)** {SILMEEW2X, SILMEEBTYPE} *(ECG(HR(IBI(RMSSD, SDNN)), HRV), PPG(PR, PTT), ST)*.	**(Q. FORMAIS)** {HEALTHYOFFICE} *(MOOD, EMOTIONS)*.	{HRVAS} *(HRV)* and {HAR} *(ACC)*.
Basu et al. (Basu et al., 2016)	**(T. SLIGHTLY OBSTRUCTIVE)** {BIOHARNESS} *(ECG, HR, PR, RESP(RR))*. **(T. OBSTRUCTIVE)** {ML870, FE116, ML135, ML309} *(EDA, ST)* and {Undefined(EMG)} *(EMG)*.		{LABCHART}.
Aracena et al. (Aracena et al., 2016)	**(T. OBSTRUCTIVE)** {EL1000} *(PUPIL, GAUZE)*.		
Adams & Robinson (Adams & Robinson, 2015)	**(T. NON-OBSTRUCTIVE)** {FACETRACKER} *(FACS (HEAD, EYELIDS, EYEBROWS, CHEEKS, EYES, NOSE, WRINKLES, LIPS, CHIN, JAW), GAZE)*.		
Turan et al. (Turan et al., 2015)	**(T. NON-OBSTRUCTIVE)** {PICTURES, VIDEO} *(FACE, EYES).*		
Korkmaz & Atasoy	**(T. NON-OBSTRUCTIVE)** {AUDIO} *(SPEECH, VOLUME)*.		

(Korkmaz & Atasoy, 2015)			
Lalitha et al. (Lalitha et al., 2015)	**(T. NON-OBSTRUCTIVE)** {AUDIO} *(SPEECH, PITCH and VOLUME)*.		
Singh et al. (Singh et al., 2015)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(SHOULDERS, HANDS)*.		
Murali et al. (Murali et al., 2015)	**(T. OBSTRUCTIVE)** {MURALI} *((ECG, ICG)(PEP, PTT), NIBP, EDA, RESP(RR))*.		
Jaques et al. (Jaques et al., 2015)	**(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, SCREEN, LOCAL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA, ST, ACC)*.	**(Q. INFORMAL)** {INFORMAL} *(HAPPY, ACADCL, ACADEX, ACADST, PHYSI, SOCIAL, CAFFEI, ALCOH, DRUGS, STRESS, HEALTH, ENERGY, ALERT, CALM, SLEEP, NAP)*.	
Cruz et al. (Cruz et al., 2015)	**(T. OBSTRUCTIVE)** {MOBILAB} *(EOG)*.		
Saha et al. (Saha et al., 2014)	**(T. NON-OBSTRUCTIVE)** {KINECT} *(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN, ACC)*.		{KINECT-SDK}.
Matiko et al. (Matiko et al., 2014)	**(T. OBSTRUCTIVE)** {Undefined(EEG)} *(EEG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	
Bogomolov et al. (Bogomolov et al., 2014)	**(T. NON-OBSTRUCTIVE)** {APP} *(CALL, SMS, PROXIMITY)* and {EXISTINGDATA} *(WEATHER)*.	**(Q. FORMAIS)** {BFIPT} *(PERSON)*. **(Q. INFORMAL)** {INFORMAL} *(STRESS)*.	
Agrawal et al. (Agrawal et al., 2013)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(EYES, MOUTH, LIPS, SKIN)*.		
Soleymani et al. (Soleymani et al., 2013)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH)*. **(T. OBSTRUCTIVE)** {ACTIVEII} *(EEG)*.		{OBSERVATION} *(EMOTIONS)*.
Vermun et al. (Vermun et al., 2013)	**(T. NON-OBSTRUCTIVE)** {KINECT} *(HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP, KNEES)*.		
Kusserow et al. (Kusserow et al., 2013)	**(T. SLIGHTLY OBSTRUCTIVE)** {TALKASSIST} *(HR(HRV), EDA, ACC, ST)*, {KUSSEROW2} *(ECG(HR), ACC)*, {KUSSEROW3} *(ECG(HR), ACC)* and {KUSSEROW4} *(HR, ACC)*.	**(Q. INFORMAL)** {INFORMAL} *(STRESS, MOOD)*.	
Alzoubi et al. (Alzoubi et al., 2013)	**(T. OBSTRUCTIVE)** {MP150} *(ECG(HRV), EMG, EDA, RESP)*.	**(Q. FORMAIS)** {AFFECTGRID} *(EMOTIONS)*.	{ACQK}.
Nawasalkar et al. (Nawasalkar et al., 2013)	**(T. OBSTRUCTIVE)** {Undefined(NIBP), Undefined(RESP)} *(NIBP, RESP(RR))*.		
Sano & Picard	**(T. SLIGHTLY OBSTRUCTIVE)**	**(Q. FORMAIS)**	

(Sano & Picard, 2013b)	{AFFECTIVAQ} *(EDA, ACC)* and {FUNF} *(CALL, SMS, LOCAL, SCREEN)*.	{PSS} *(STRESS)*, {PSQI} *(SLEEP)* and {BFIPT} *(PERSON)*. **(Q. INFORMAL)** {INFORMAL} *(SLEEP, ELECTR, HEALTH, MOOD, ALERT, TIRED, STRESS, NAP, CAFFEI, ALCOH)*.	
Raudonis (Raudonis, 2013)	**(T. SLIGHTLY OBSTRUCTIVE)** {RAUDONIS1} *(GAZE, EYES, PUPIL)*.		
Kawai et al. (Kawai et al., 2013)	**(T. NON-OBSTRUCTIVE)** {XCEI30} *(PUPIL)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	{DS400}.
Babiker et al. (Babiker et al., 2013)	**(T. NON-OBSTRUCTIVE)** {TX300} *(EYES, GAZE, PUPIL)*.	**(Q. FORMAIS)** {PANES-X} *(EMOTIONS)*.	
LikamWa et al. (LiKamWa et al., 2013)	**(T. NON-OBSTRUCTIVE)** {MOODSCOPE} *(SMS, EMAIL, CALL, APPS, BROWSER, LOCAL)*.	**(Q. FORMAIS)** {CIRCUMPLEX} *(MOOD)*.	
Murad & Malkawi (Murad & Malkawi, 2012)	**(T. OBSTRUCTIVE)** {Undefined(EEG), Undefined(HR), Undefined(HRV), Undefined(PEP), Undefined(SV), Undefined(BP), Undefined(RESP), Undefined(EDA), Undefined(nSRR), Undefined(ST)} *(EEG, HR, HRV, PEP, SV, BP(SBP, DBP), RESP(VT, ROS, RR), EDA, nSRR, ST)*.		
C. Y. Chang et al. (Chang et al., 2012)	**(T. OBSTRUCTIVE)** {ML870} *(ECG, BVP, PR, EDA)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*.	
Bauer & Lukowicz (Bauer & Lukowicz, 2012)	**(T. NON-OBSTRUCTIVE)** {APP} *(LOCAL, PROXIMITY, CALL, SMS)*.		
Yang & Bhanu (S. Yang & Bhanu, 2011)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(HEAD, FACE)*.		{EAI}.
Dhall et al. (Dhall et al., 2011)	**(T. NON-OBSTRUCTIVE)** {PICTURES, VIDEO} *(FACE)*.		
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(PUPIL)*. **(T. OBSTRUCTIVE)** {ML870} *(ECG(HRV), PPG)*.		
Hernandez et al. (Hernandez et al., 2011)	**(T. NON-OBSTRUCTIVE)** {EXISTINGDATA} *(CALL)*. **(T. SLIGHTLY OBSTRUCTIVE)** {AFFECTIVAQ} *(EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(STRESS)*.	{OBSERVATION} *(STRESS)*.
N. Lane et al. (N. Lane et al., 2011)	**(T. NON-OBSTRUCTIVE)** {BEWELL} *(SLEEP, PHYSI, TALK, LOCAL, ACC)*.	**(Q. INFORMAL)** {INFORMAL} *(DEPRESSION, SLEEP, WELLBEING)*.	{HAR}.
H. Wang et al. (H. Wang et al., 2010)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(EYES)*.		
Bos (Bos, 2010)	**(T. SLIGHTLY OBSTRUCTIVE)** {BQPET} *(EEG)*.		{BIOEXPLORER}.
Y. Liu et al. (Y. Liu et al., 2010)	**(T. OBSTRUCTIVE)** {EPOC} *(EEG)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)**	{EPOC-SDK}.

		{INFORMAL} *(EMOTIONS)*.	
Setz et al. (Setz et al., 2010)	**(T. SLIGHTLY OBSTRUCTIVE)** {EMOTIONBOARD} *(EDA)*.		
J. Kim & Andre (J. Kim & André, 2008)	**(T. OBSTRUCTIVE)** {PROCOMP} *(EMG, EDA, ECG(HR, HRV), RESP(RR, BRV))*.		
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	**(T. OBSTRUCTIVE)** {HEALTHLAB} *(RESP(RR, RDEP), EDA, ECG(HR, HRV, IBI), EMG, ST)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	**(T. OBSTRUCTIVE)** {ASL504} *(PUPIL)*, {S71-22} *(EDA)* and {S75-01} *(ECG(HR, IBI))*.		
Gunes & Piccardi (Gunes & Piccardi, 2007)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, CHEEKS, FOREHEAD, JAW, NOSE, HANDS, FINGERS, FISTS, PALMS, SHOULDERS, NECK)*.		
Castellano et al. (Castellano et al., 2007)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(ARMS)*.		
Mandryk & Atkins (Mandryk & Atkins, 2007)	**(T. NON-OBSTRUCTIVE)** {VIDEO, AUDIO}. **(T. OBSTRUCTIVE)** {PROCOMP} *(EDA, ECG(HR), EMG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	{BIOGRAPH}.
Sebe et al. (Sebe et al., 2006)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(HEAD, EYEBROWS, EYELIDS, MOUTH)* and {AUDIO} *(VOLUME, SPEECH, PITCH)*.		
Zhai & Barreto (Zhai & Barreto, 2006)	**(T. OBSTRUCTIVE)** {Undefined(EDA), Undefined(BVP), Undefined(PUPIL), Undefined(ST), Undefined(LIGHT), Undefined(TEMP)} *(EDA, BVP(IBI), PUPIL, ST, LIGHT, TEMP)*.		
J. A. Healey & Picard (J. A. Healey & Picard, 2005)	**(T. NON-OBSTRUCTIVE)** {VIDEO}. **(T. OBSTRUCTIVE)** {FLEXCOMP} *(ECG(HR, HRV), EMG, EDA, RESP)*.	**(Q. INFORMAL)** {INFORMAL} *(STRESS)*.	{OBSERVATION} *(STRESS)*.
Herbon et al. (Herbon et al., 2005)	**(T. SLIGHTLY OBSTRUCTIVE)** {HERBON} *(PUPIL)*. **(T. OBSTRUCTIVE)** {Undefined(EDA), Undefined(ST), Undefined(HR)} *(EDA, ST, HR)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*. **(Q. INFORMAL)** {INFORMAL} *(GENDER, AGE, HEALTH, TECHEXPERT)*.	
Partala et al. (Partala et al., 2005)	**(T. OBSTRUCTIVE)** {MODEL15} *(EMG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*	{LINK15}.
Van Eck et al. (van Eck et al., 2005)	**(T. OBSTRUCTIVE)** {CORTISOL, SALIVETTE} *(CORT)*.	**(Q. FORMAIS)** {PSS} *(STRESS)*, {LTE} *(LIFEEVENTS)*, {LDI} *(DIFFICULTIES)*, {PSC} *(HEALTH)*, {SDS} *(DEPRESSION)*,	

		{STAI} *(ANXIETY)* and {STAS} *(ANGER)*. **(Q. INFORMAL)** {INFORMAL} *(MOOD, WELLBEING, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH, EMOTIONS).*	
Busso et al. (Busso et al., 2004)	**(T. NON-OBSTRUCTIVE)** {VIDEO} *(FOREHEAD, EYEBROWS, EYES, CHEEKS) and* {AUDIO} *(PITCH, VOLUME)*.		
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	**(T. SLIGHTLY OBSTRUCTIVE)** {JAWBONE} *(EDA, HR, ST)*.	**(Q. INFORMAL)** {INFORMAL} *(AGE, GENDER, ETHNICITY, EMOTIONS)*.	
K. H. Kim et al. (K. H. Kim et al., 2004)	**(T. OBSTRUCTIVE)** {MP100} *(ECG(HR,HRV), PPG, ST, EDA)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*	
Haag et al. (Haag et al., 2004)	**(T. OBSTRUCTIVE)** {PROCOMP} *(EMG, EDA, ST, PPG(BVP(HR)), ECG(HR), RESP)*.		
Partala & Surakka (Partala & Surakka, 2003)	**(T. OBSTRUCTIVE)** {ASL4000} *(PUPIL)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*	{PSYSCOPE}.
C J Harmer et al. (C J Harmer et al., 2003)	**(T. OBSTRUCTIVE)** {MANUAL} *(SEROT)*.	**(Q. FORMAIS)** {BFS} *(MOOD)*. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS, ENERGY, ANXIETY).*	{INTERVIEW}.
Nwe et al. (Nwe et al., 2001)	**(T. NON-OBSTRUCTIVE)** {AUDIO} *(SPEECH)*.		
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	**(T. OBSTRUCTIVE)** {ORION, SALIVETTE} *(CORT)* and {Undefined(EMG)} *(EMG)*.	**(Q. INFORMAL)** {INFORMAL} *(EMOTIONS).*	
Jennifer a Healey (Jennifer a Healey et al., 2000)	**(T. OBSTRUCTIVE)** {PROCOMP} *(EDA, PPG(BVP(HR)), EMG, RESP)* and {Undefined(*ECG*)} *(ECG(HR, HRV))*.	**(Q. INFORMAL)** {INFORMAL} *(STRESS).*	
Vrijkotte et al. (Vrijkotte et al., 2000)	**(T. OBSTRUCTIVE)** {S90207} *(BP(SBP, DBP))* and {VU-MAS} *(ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC)*.	**(Q. FORMAIS)** {ERI} *(STRESS)* and {POMS} *(MOOD)*. **(Q. INFORMAL)** {INFORMAL} *(PERSON, AGE, WORKYEARS, ACADDG, PHYSI, BMI, HEIGHT, WEIGHT, WAIST, CAFFEI, ALCOH, SMOKING)*.	
Ritz et al. (Ritz et al., 2000)	**(T. OBSTRUCTIVE)** {SIREGNOSTFD5} *(ROS)*, {FH3803, GMCS5} *(VT, RR)*, {FINAPRESS4} *(HR, BP(SBP, DBP))* and {Undefined(EDA)} *(EDA)*.	**(Q. FORMAIS)** {SAM} *(EMOTIONS)*, {AIM, TAS, MCSDS}. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	
L. S. Chen et al. (L. S. Chen et al., 1998)	**(T. NON-OBSTRUCTIVE)** {AUDIO} *(SPEECH, PITCH)* and		

	{VIDEO} *(EYES, EYEBROWS, MOUTH, WRINKLES, FROWN)*.		
J. Healey & Picard (J. Healey & Picard, 1998)	**(T. OBSTRUCTIVE**) {PROCOMP} *(EDA, PPG(BVP(HR)), RESP, EMG)*.		
Rajita Sinha (Rajita Sinha, 1996)	**(T. OBSTRUCTIVE)** {78B} *(BP(SBP, DBP))* and {Undefined(ECG), Undefined(EDA), Undefined(ST), Undefined(EOG), Undefined(EMG)} *(ECG(HR), EDA, ST, EOG, EMG)*.	**(Q. FORMAIS)** {MMPI, QMI, TAS, BDI, STAI} and {DES} *(EMOTIONS)*. **{Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	{INTERVIEW}.
Scott R. Vrana (Scott R. Vrana, 1993)	**(T. OBSTRUCTIVE)** {S75-01} *(ECG(HR))*, {Undefined(*EMG*)} *(EMG)* and {S71-22} *(EDA)*.	**(Q. FORMAIS)** {QMI}. **(Q. INFORMAL)** {INFORMAL} *(EMOTIONS)*.	
R Rinha et al. (R Sinha et al., 1992)	**(T. OBSTRUCTIVE)** {Undefined(BP)} *(BP(SBP, DBP))*, {Undefined(ICG)} *(ICG(SV, CO, PVR, PEP, LVET))*, {Undefined(ECG)} *(ECG(HR))* and {Undefined(PCG)} *(PCG)*.	**(Q. FORMAIS)** {QMI, TAS} and {DES} *(EMOTIONS)*.	{INTERVIEW, OBSERVATION}.

() represents a raw signal; and {} an instrument.

4. PRE-PROCESSING

The accuracy of emotional detection systems has been increasing as a result of the diversification of context data collected, the evolution of applied techniques (e.g. image processing, speech recognition, natural language processing, dynamics in the use of input devices (cf. keyboard, mouse and touch-screen)), technological evolution at the sensor level (Bakhtiyari & Husain, 2014), and the evolution of Artificial Intelligence algorithms, namely those that have been used to support the resolution of real human problems (Gama, Carvalho, Faceli, Lorena, & Oliveira, 2012).

One of the most important requirements for machine learning algorithms is the ability to handle imperfect datasets (Gama et al., 2012). A dataset can be defined as a set composed of objects (instances, records or observations) and attributes (fields or characteristics of each object). An object represents a physical or abstract concept and is described by a set of attributes (key-value tuples) that summarize its characteristics. Each object represents an occurrence of data and each attribute a property that characterizes or identifies the object (Gama et al., 2012). There are datasets of various types: time series that record data occurrences chronologically (e.g. ST records over several days), graphs (e.g. paths traveled), transactions (e.g. purchase records) (Gama et al., 2012), etc. Attributes can also be of various types (quantitative or qualitative) and scales (operations possible to perform on the values). Quantitative attributes are numerical, and can be discrete allowing a countable number of values (e.g. number of CALLs, ages), or continuous being able to take on an infinite number of real values (e.g. distances, weights, etc.). Numerical attributes are usually accompanied by a unit to contextualize the measurement (e.g. meter, kilogram, etc.). Qualitative attributes are represented by a finite number of symbols or names. As for the scale, attributes can be classified as: nominal (i.e. labels with no ordering relationship among themselves (e.g. {Portugal, Spain, France})); ordinal (i.e. where the categories assume an order (e.g. {few, some, many})); interval (i.e. values are represented by intervals (e.g. [20; 38[, [38; 44])) and rational (i.e. absolute values that represent a measure together with a unit (e.g. 30.5°C, 10.5m, etc.)) (Gama et al., 2012).

Typically the performance of algorithms improves with increasing number of objects and decreases with increasing amount of attributes (Gama et al., 2012). However, there are other factors that can affect the performance of algorithms and impair the induction processes: diversity of dimensions or shapes; noise or imperfections of the signal; incorrect or inconsistent values; missing or redundant data; etc. (Gama et al., 2012) (S. Zhang, Zhang, & Yang, 2010). Pre-processing techniques allow to identify and reduce the occurrence of problems in datasets (Gama et al., 2012). The main goal of these techniques is to increase the efficiency of the data to optimize the processing of the algorithms (e.g. normalizing the light intensity and size of images, reducing the dimensionality of datasets, etc.) (Mokhayeri & Toosizadeh, 2011), and create models that are more faithful to reality (Gama et al., 2012). However, pre-processing techniques can also be used to make the data suitable for the application of a particular type of algorithm (Gama et al., 2012). There is no set order for the application of pre-processing techniques (Gama et al., 2012). Thus, the input of a technique can be the dataset collected from the context (i.e. raw data), or the output resulting from the application of any other technique. The output can be defined as the result of applying the algorithm of the applied technique, to the input of the algorithm.

Gama et al. (Gama et al., 2012) categorized the pre-processing tasks into several groups: i) integration of data from various sources; ii) sampling techniques to optimize the dataset content (objects and attributes); iii) balancing the number of objects between classes because of the sensitivity of some algorithms to processing datasets with unbalanced classes; iv) data cleaning (e.g. noise removal, reconstruction of missing, incomplete or inconsistent data); v) dimensional reduction to promote algorithm efficiency (e.g. reduction of redundant, irrelevant or inconsistent attributes); and vi) data transformation (e.g. sign normalization, type conversion, etc.) (Gama et al., 2012).

Based on the categorization of Gama et al. (Gama et al., 2012) and the reality of the investigations considered in this literature survey, we decided to divide the pre-processing techniques into the following groups: i) dataset maintenance which includes techniques related to data quality; ii) signal maintenance which encompasses techniques such as normalization, segmentation and new signal generation; and iii) sampling and meta-information where sampling, balancing and data labeling techniques are included.

The following table summarizes the pre-processing techniques identified in this literature survey.

ID	DESCRIPTION	GROUP	CATEGORY
DATASET MAINTENANCE			
ADABOOST	Adaboost Algorithm.	Dimensional reduction and object redundancy	Dimensional reduction
AGGREGATION	Combining several dependent attributes into one.	Dimensional reduction and object redundancy	Dimensional reduction
BESTFIRST	Best-First Search.	Dimensional reduction and object redundancy	Dimensional reduction
BOGOMOLOV	Algorithm adapted by Bogomolov et al. (Bogomolov et al., 2014).	Dimensional reduction and object redundancy	Dimensional reduction
CONSISTENCY	Evaluating the level of data consistency.	Noise, incomplete and inconsistent data	Inconsistent Data
CORRELATION	It allows you to measure the strength of the relationship between variables.	Dimensional reduction and object redundancy	Dimensional reduction
DCC	Discriminant - Analysis of Canonical Correlations.	Dimensional reduction and object redundancy	Dimensional reduction
DISCARDDATA	Removing objects because they contain missing data.	Noise, incomplete and inconsistent data	Incomplete Data
DISTINCTOBJ	Assumption of only distinct objects.	Dimensional reduction and object redundancy	Object Redundancy
-DUPLICATE	Removal of redundant objects (e.g. duplicate collections).	Dimensional reduction and object redundancy	Object Redundancy
-EYEBLINK	Blink removal.	Noise, incomplete and inconsistent data	Noise
FAKEDATA	Artificial data generation to fill in missing data.	Noise, incomplete and inconsistent data	Incomplete Data
FDA	Fisher's Discriminant Analysis.	Dimensional reduction and object redundancy	Dimensional reduction
-FRAMES	Removal of redundant VIDEO frames.	Dimensional reduction and object redundancy	Object Redundancy

GA	Genetic Algorithm.	Dimensional reduction and object redundancy	Dimensional reduction
LDA	Linear Discriminant Analysis (LDA).	Dimensional reduction and object redundancy	Dimensional reduction
MANADJUST	Manual data editing.	Noise, incomplete and inconsistent data	Other
MANINSERT	Manual data entry.	Noise, incomplete and inconsistent data	Other
MANSELECT	Manual selection of irrelevant or relevant attributes.	Dimensional reduction and object redundancy	Dimensional reduction
MITIGATION	Attenuation of external effects (i.e. interference) to the signal.	Noise, incomplete and inconsistent data	Other
MURALI	Specific algorithm created by Murali et al. (Murali et al., 2015).	Dimensional reduction and object redundancy	Dimensional reduction
-NOISE	Noise reduction or removal.	Noise, incomplete and inconsistent data	Noise
NULL	Assumption of lack of data.	Noise, incomplete and inconsistent data	Incomplete Data
-OUTLIERS	Removing discrepant values in the distribution.	Noise, incomplete and inconsistent data	Inconsistent Data
PCA	Principal Component Analysis (PCA).	Dimensional reduction and object redundancy	Dimensional reduction
-PEAK	Identification and removal of peaks identified as possible noise artifacts.	Noise, incomplete and inconsistent data	Noise
RELIABILITY	Evaluation of the level of reliability of the data.	Noise, incomplete and inconsistent data	Incomplete Data
-SACCADE	Removal of rapid eye movements.	Noise, incomplete and inconsistent data	Noise
SBS	Sequential Backward Selection (SFS).	Dimensional reduction and object redundancy	Dimensional reduction
SCATTER	Diagram that allows you to visually analyze in Cartesian space the redundancy between attributes.	Dimensional reduction and object redundancy	Dimensional reduction
SFFS	Sequential Floating Forward Selection.	Dimensional reduction and object redundancy	Dimensional reduction
SFS	Sequential Forward Selection (SFS).	Dimensional reduction and object redundancy	Dimensional reduction
SLPP	Supervised Locality Preserving Projection.	Dimensional reduction and object redundancy	Dimensional reduction
TOLERANCE	Assumption of data tolerances or data insertion moments.	Noise, incomplete and inconsistent data	Incomplete Data
WFS	Wrapper Feature Selection.	Dimensional reduction and object redundancy	Dimensional reduction
X^2	Chi-square.	Dimensional reduction and object redundancy	Dimensional reduction
SIGNAL MAINTENANCE			

2D-DISCRETE	Conversion from two-dimensional to discrete space.	Signal and data type conversion	Data Type Conversion
3D2D	Conversion from three to two dimensions and vice versa.	Signal and data type conversion	Signal conversion
ABPF	Adaptive bandpass filter.	Normalization, amplification and filters	Filters
ADL	Identification of everyday tasks (e.g. sleeping, sitting, walking, etc.).	Segmentation and new signal generation	Generating a new signal
BANDS	Signal segmentation into bands.	Segmentation and new signal generation	Signal segmentation
BINARY	Binarization of images.	Signal and data type conversion	Signal conversion
GMP	Bandpass filter.	Normalization, amplification and filters	Filters
COLORSEG	Color segmentation.	Segmentation and new signal generation	Signal segmentation
D^2Y/DX^2	Sign differentiation in the second derivative.	Segmentation and new signal generation	Generating a new signal
DWT	Discrete Wavelet Transform.	Segmentation and new signal generation	Signal segmentation
DY/DX	Sign differentiation in the first derivative.	Segmentation and new signal generation	Generating a new signal
FD	Fractal Dimension.	Signal and data type conversion	Signal Conversion
FOURIER	Signal conversion from the time domain to frequencies.	Signal and data type conversion	Signal Conversion
GREYSCALE	Converting PICTURES to gray scales.	Signal and data type conversion	Signal conversion
HHT	Hilbert-Huang Transform.	Signal and data type conversion	Signal conversion
HPF	High-pass filter.	Normalization, amplification and filters	Filters
IMGALIGN	Normalization of image alignment (e.g. eye position).	Normalization, amplification and filters	Standardization
-IMGBKG	Removal of the PICTURES background after recognition of shapes or relief points.	Segmentation and new signal generation	Signal segmentation
IMGCONTRAST	Normalization of contrast in images.	Normalization, amplification and filters	Standardization
IMGINTENSITY	Normalization of light intensity in images.	Normalization, amplification and filters	Standardization
IMGSIZE	Image size normalization.	Normalization, amplification and filters	Standardization
INTEGRATION	Integration or fusion of data from various sources.	Segmentation and new signal generation	Other
INTERVALSPLIT	Dividing the signal into time intervals.	Segmentation and new signal generation	Signal segmentation
KAWAI2	Technique adapted by Kawai et al. (Kawai et al., 2013).	Normalization, amplification and filters	Standardization
LPF	Low-pass filter.	Normalization, amplification and filters	Filters

N-N	Segmentation of physiological signals into N-N intervals.	Segmentation and new signal generation	Signal segmentation
NORM	Normalization of data (e.g. amplitudes of numerical attributes).	Normalization, amplification and filters	Standardization
PATHSTAKEN	Creating data about paths traveled.	Segmentation and new signal generation	Generating a new signal
QUALI-QUANTI	Converting qualitative values to quantitative values.	Signal and data type conversion	Data Type Conversion
R-R	Segmentation of physiological signals into R-R intervals.	Segmentation and new signal generation	Signal segmentation
SIGAMP	Signal Amplification	Normalization, amplification and filters	Amplification
SIGSMOOTH	Signal smoothing.	Normalization, amplification and filters	Other
SIGSPLIT	Signal separation (e.g. ECG and ICG).	Segmentation and new signal generation	Signal segmentation
TASKSPLIT	Task identification (e.g. ski jumpers).	Segmentation and new signal generation	Generating a new signal
USUALPLACES	Creating data about places frequented.	Segmentation and new signal generation	Generating a new signal
VIDEO-PICS	Converting VIDEO to PICTURES.	Signal and data type conversion	Signal conversion
ZHAO1	Author Zhao et al. specific technique to emphasize the signal to extract (Zhao et al., 2016).	Normalization, amplification and filters	Other
ZHAO2	Segmentation technique adapted by Zhato et al. (Zhao et al., 2016).	Segmentation and new signal generation	Signal segmentation
ZTRANSFORM	Signal conversion from the time domain to frequencies.	Signal and data type conversion	Signal Conversion
SAMPLING AND META-INFORMATION			
+ARTIFICIALDATA	Synthetic data generation.	Balancing and labeling	Balancing
DECIMATION	Downsampling.	Sampling Techniques	N/A
INTENTIONAL	The sampling criterion is intentionally set by the researcher.	Sampling Techniques	N/A
LABELING	Enriching data by placing tags with meta-information.	Balancing and labeling	Labeling
RANDOM	The selection of objects is done randomly (e.g. by drawing lots).	Sampling Techniques	N/A
SPREADSUBSAMPLE	Balancing between classes is done by applying a WEKA downsampling technique.	Balancing and labeling	Balancing
STRATIFIED	The selection of objects is made on the basis of previously defined layers.	Sampling Techniques	N/A
SYSTEMATIC	The selection is made at each r object occurrence.	Sampling Techniques	N/A
OTHER TECHNIQUES AND INSTRUMENTS			

ANOVA	Analysis of variance to find differences between groups or experiments.	N/A	Data representation
AUBT	Augsburg Biosignal Toolbox.	N/A	Instruments
BLINKDETECT	Blink detection in VIDEO.	N/A	Support Techniques
CLUSTERING	Defining clusters in PICTURES for the purpose of identifying objects or image zones.	N/A	Support Techniques
COLORCORR	Color Correlogram.	N/A	Data representation
CROP	Cut out PICTURES.	N/A	Support Techniques
EEGLAB	Instrument for EEG signal maintenance.	N/A	Instruments
EYESWEB	Instrument for real-time body motion monitoring.	N/A	Instruments
FEELTRACE	Instrument to simultaneously track and provoke emotions.	N/A	Instruments
FINDREGION	Detection of regions or edges in images.	N/A	Support Techniques
GLM	An instrument to analyze the relationship between variables.	N/A	Instruments
HAC	Hierarchical Agglomerative Clustering.	N/A	Instruments
HISTOGRAM	Histogram.	N/A	Data representation
KAWAI1	Specific technique by Kawai et al. (Kawai et al., 2013) to attenuate brightness differences in images.	N/A	Support Techniques
KHRV	KUBIOS HRV (HRV analysis tool).	N/A	Instruments
LANE1	Specific technique by Lane et al. (N. Lane et al., 2011) for estimating sleep time based on smartphone battery recharge times.	N/A	Other
MATLAB	Mathworks Matlab platform.	N/A	Instruments
MORPHOPS	Morphological operations on PICTURES.	N/A	Support Techniques
MOTIONDETECT	Motion detection of objects or people.	N/A	Support Techniques
ORIGIN	OriginLab Platform.	N/A	Instruments
PEAKDETECT	Detection of signal peaks (e.g. breathing cycles).	N/A	Other
RAUDONIS2	Raudonis' specific technique (Raudonis, 2013) to consider the variation of luminosity in PUPIL.	N/A	Support Techniques
SI-SSM	Index-based Statistical shape model.	N/A	Support Techniques

SPARSEREP	Sparse Representation.	N/A	Data representation
TTEST	Statistical analysis of the means of two sets.	N/A	Data representation
WEKA	Waikato Environment for Knowledge Analysis.	N/A	Instruments
YANG1	Specific technique by Yant et al. (S. Yang & Bhanu, 2011) to represent faces in avatars.	N/A	Data representation
ZFACE	Instrument for tracking facial expressions.	N/A	Instruments

For easier understanding, in this document the term RAW will be used to identify the original signal collected from the context, and the name of the applied technique to specify the output signal of that technique. In addition, in cases where it is possible to identify the chaining of the applied techniques, the notation [original signal [resultant signal]] will be used to indicate the authors' perception of the chaining of the signals used. Thus (EDA) [RAW] indicates the EDA raw data, (EDA) [RAW, LPF], specifies the RAW signal and the LPF signal of the EDA signal, and EDA [RAW [LPF [DY/DX]]] refers to the signal resulting from the application of DY/DX to the LPF signal, whose input was the EDA data collected from the context. For simplicity of notation and when implied, the term RAW may be omitted, the curly bracket itself meaning the indication of the RAW version of the signal. Thus (EDA) [RAW[LPF[DY/DX]]] is equivalent to (EDA) [LPF[DY/DX]].

Just as there is no predefined order for the use of pre-processing techniques (Gama et al., 2012), techniques can also be applied on the dataset already supplemented with additional properties. The extracted properties will be discussed in section 5. However, because it is necessary to specify the application of pre-processing techniques on extracted properties and datasets complemented with extracted properties, we introduce in advance the notation to be used for their representation. Thus, (ACC)<MAG>[NORM] represents the application of the NORM pre-processing technique to the magnitude (MAG) property extracted from the ACC RAW signal. The notation <ACC> represents in a simplified form the final set of attributes (i.e. original and extracted properties) of the ACC signal (e.g. <ACC, EDA> [CORRELATION] indicates the application of the CORRELATION technique to the base attributes and extracted properties of the ACC and EDA signals). Since there are several investigations that focus on the application of pre-processing techniques on extracted properties, to avoid constantly mixing up the explanation of terms that are formally presented in the introduction of section 5, we refer to that section when tokens used within <> are not self-identifiable by name alone.

4.1. DATASET MAINTENANCE

This section discusses techniques related to dataset data quality and redundancy. Data maintenance techniques aim to detect and correct (or minimize) problems in datasets. The data can present several types of problems: i) unexpected values (e.g. a person's age is higher than possible); ii) inconsistent values (i.e. attributes with contradictory values for the same object); iii) redundant values (e.g. values of an attribute are the same in all objects or the existence of attributes whose value can be taken from another); iv) incomplete data (e.g. some attributes with unfilled data); etc. (Gama et al., 2012).

Based on the literature under review, the pre-processing techniques related to dataset maintenance were divided into the following categories: i) noise, incomplete and inconsistent data; and ii) dimensional reduction and object redundancy.

4.1.1. Noise, incomplete and inconsistent data

The context data collected by the sensors may contain noise created by external interferences such as electrostatics, muscle movements, etc. These noises must be removed or mitigated from the input signal before it is used as the basis for processing (Jerritta et al., 2011).

This section includes pre-processing techniques that aim to increase the quality of the dataset. Context data collection processes may result in the presence of data in the dataset that does not belong to the distribution that generated it. This noise may result from bad data filling by the user or by interferences that occur during the context introspection process. There are several techniques used at this level: noise reduction **[-NOISE]** is used in several signal types (e.g. Mokhayeri et al. (Mokhayeri & Toosizadeh, 2011) and Aracena et al. (Aracena et al., 2016) used techniques to remove noise from PUPIL images, Sano & Eng. used an algorithm developed by their research group for artifact detection in the EDA signal (Sano & Eng, 2016), Bos used LPF and HPF to remove noise and artifacts from the EEG signal (e.g. eye movement) (Bos, 2010), and Kim et al. used ABPF to remove artifacts and LPF to remove noise (J. Kim & Andre, 2008)); the removal of signal peaks **[-PEAK]** identified as possible noise artifacts (e.g. Jaques et al. (Jaques et al., 2015)); the removal of blinking in VIDEO **[-EYEBLINK]** (e.g. Mokhayeri et al. (Mokhayeri & Toosizadeh, 2011) and Aracena et al. (Aracena et al., 2016)); and rapid eye movements (i.e. saccades) are studied by some researchers (e.g. Perdiz et al. (Perdiz et al., 2017)) and treated as noise by others because they cause interference in the studied signals **[-SACCADE]** (e.g. Aracena et al. (Aracena et al., 2016.)).

The dataset may also contain incomplete data. Missing attributes may result from the user forgetting or deciding not to fill them in, or because of problems in the context gathering processes. To address the problems of incomplete data, researchers use various pre-processing techniques: Jaques et al. manually removed **[DISCARDDATA]** the SCREEN events with less than five daily uses (Jaques et al.)) and Soleymani et al. discarded some facial response videos because the annotators could not get a sense of the valence felt by the participants based on the expressions (Soleymani et al., 2013); Lee et al. generated data to solve the problem of partial transitions of facial expressions [**FAKEDATA**] (S. H. Lee et al., 2016), and Jaques et al. also generated data (i.e. FAKEDATA) through interpolation to fill in missing data from LOCAL (Jaques et al., 2015); Jaques et al. also used the assumption of no data by giving a representative gap value to the attributes concerned **[NULL]**; Zenonos et al. decided to tolerate **[TOLERANCE]** delays in their participants' annotations within a given time window (Zenonos et al., 2016); and LikamWa et al. evaluated response rates to determine the level of reliability of the collected data **[RELIABILITY]** (LiKamWa et al., 2013) and Healey et al. tested the level of RELIABILITY of the coders' annotations from their research using Cronbach's alpha (L. J. Cronbach, 1951) (L. Cronbach, 1951) (J. A. Healey & Picard, 2005).

Sometimes the dataset may also contain inconsistent data (i.e. contradictory or discrepant values) (e.g. a person weighing 130kg at the age of 3 years) (Gama et al., 2012). At this level, the authors use the following techniques: Babiker et al. used a moving average to remove **outliers [-OUTLIERS]** (Babiker et al., 2013); and LikamWa et al. evaluated the consistency **[CONSISTENCY]** of the data collected about MOOD, to screen for abnormal variations over time (LiKamWa et al., 2013) (Batson, Shaw, & Oleson, 1992) (Beedie, Terry, & Lane, 2005).

Also included in this section are other techniques related to the attenuation **[MITIGATION]** of external effects on the signal (e.g. Jaques et al. used ACC and ST to diminish the effect of physical activity on the collected EDA signal (Jaques et al., 2015), Kawai et al. used signal averaging of the PUPIL diameter to decrease Signal-to-Noise RATIO caused by presenting multiple images (Kawai et al., 2013), and Babiker et al. preferred to use sound stimuli to avoid interference from image luminance (Babiker et al., 2013)). Finally, also considered in this section are techniques used for direct data insertion or editing by users or researchers: Kawai et al. manually corrected the DIAMETER of PUPIL when the system measured it incorrectly **[MANADJUST**] (Kawai et al., 2013); Lane et al. allowed participants in their experiment, in addition to being able to correct inference errors from the application they created (i.e. MANADJUST), to also manually insert activities not inferred by BEWELL **[MANINSERT**] (N. Lane et al., 2011); Chen et al. manually entered information about eye and mouth movement (L. S. Chen et al., 1998) and trained assistants of Sinha et al. manually entered the values given by the ICG (R Sinha et al., 1992) (i.e. MANINSERT).

RESEARCH	DATASET MAINTENANCE	
	NOISE, D. INC. AND INC.	OTHER
S. H. Lee et al. (S. H. Lee et al., 2016)	(FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)) [FAKEDATA].	**(NORM, AMP, AND FILTER)** (EYEBROWS, EYELIDS) [NORM]. **(OTHER)** (FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH) [CLUSTERING, SPARSEREP] and (EYEBROWS, EYELIDS) [FINDREGION, CROP]. {HAC}.
Gogia et al. (Gogia et al., 2016)	(EEG) [-EYEBLINK].	**Red. dim. and red. obj:** (EEG) [-DUPLICATE]. **(BALANCING AND LABELING)** (EEG) [[[-EYEBLINK, -DUPLICATE] [LABELING]] [+ARTIFICIALDATA]].
Sano & Eng (Sano & Eng, 2016)	(EDA) [-NOISE].	**Red. dim. and red. obj:** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING]. **(OTHER)** (ACC) [MOTIONDETECT].
Zhao et al. (Zhao et al., 2016)	(RESP, HR) [-NOISE].	**(NORM, AMP, AND FILTER)** (RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF]. **(SEC. AND GER. SIGNAL)** (RESP, HR) [D2Y/DX2, ZHAO2]. **(OTHER)** (RESP) [LPF [PEAKDETECT]].
Zenonos et al. (Zenonos et al., 2016)	(MOOD, EMOTIONS) [TOLERANCE].	**(NORM, AMP, AND FILTER)** (IBI) [NORM]. **(SEC. AND GER. SIGNAL)** (IBI) [BANDS]. **(BALANCING AND LABELING)**

		(EMOTIONS) [LABELING].
Aracena et al. (Aracena et al., 2016)	(PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE].	**(NORM, AMP, AND FILTER)** (PUPIL) [LPF, NORM]. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].
Murali et al. (Murali et al., 2015) e (Padmanabhan, Murali, Rincon, & Atienza, 2015)	(ECG, ICG) [-NOISE].	<u>**Red. dim. and red. obj:**</u> (((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI]. **(NORM, AMP, AND FILTER)** (ECG, EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (ECG, ICG) [SIGSPLIT]. **(OTHER)** (ECG) [PEAKDETECT].
Jaques et al. (Jaques et al., 2015)	(EDA) [LPF [NORM [**-PEAK]]]**, (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] **and** (LOCAL) [INTEGRATION [FAKEDATA, NULL]].	<u>**Red. dim. and red. obj:**</u> (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]] and <ACC> [NORM]. **(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX]. **(BALANCING AND LABELING)** (HAPPY) [LABELING].
Soleymani et al. (Soleymani et al., 2013)	(EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE].	**(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING]. **(OTHER)** {FEELTRACE}
Kawai et al. (Kawai et al., 2013)	(PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION].	**(CONV. SINAL)** (PUPIL) [BINARY]. **(NORM, AMP, AND FILTER)** (PUPIL) <DIAMETER> [KAWAI2 [NORM]]. **(OTHER)** (PUPIL) [FINDREGION, CLUSTERING, KAWAI1].
Babiker et al. (Babiker et al., 2013)	(PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS] [FAKEDATA, DISCARDDATA]]]].	**(NORM, AMP, AND FILTER)** <PUPIL> [NORM]. **(SEC. AND GER. SIGNAL)** (PUPIL) <INTERVALSPLIT>. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC]. **(OTHER)** (PUPIL) [FINDREGION].

LikamWa et al. (LiKamWa et al., 2013)	(MOOD) [RELIABILITY, CONSISTENCY].	**<u>Red. dim. and red. obj:</u>** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(SEC. AND GER. SIGNAL)** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING]. **(OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
C. Y. Chang et al. (Chang et al., 2012)	(ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]].	**<u>Red. dim. and red. obj:</u>** (ECG, PR, BVP, EDA) [MANSELECT]. **(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(PUPIL) [-NOISE, -EYEBLINK].	**<u>Red. dim. and red. obj:</u>** <ECG(HRV), PPG, PUPIL> [GA]. **(CONV. SINAL)** (PUPIL) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (PUPIL) [IMGSIZE, IMGINTENSITY]. **(SEC. AND GER. SIGNAL)** (ECG(HRV)) [BANDS]. **(OTHER)** (PUPIL) [FINDREGION, BLINKDETECT].
Hernandez et al. (Hernandez et al., 2011)	(EDA) [-NOISE].	**(NORM, AMP, AND FILTER)** (EDA, STRESS) [NORM] and <EDA, STRESS> [NORM]. **(BALANCING AND LABELING)** (CALL) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
N. Lane et al. (N. Lane et al., 2011)	(SLEEP, PHYSI) [MANINSERT].	**(SEC. AND GER. SIGNAL)** (ACC) [ADL]. **(OTHER)** (SLEEP) [LANE1] and (SLEEP, PHYSI) [MANADJUST].
H. Wang et al. (H. Wang et al., 2010)	(EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]].	**<u>Red. dim. and red. obj:</u>** <EYES> [ADABOOST]. **(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG].

		(BALANCING AND LABELING) (EYES) [+ARTIFICIALDATA, LABELING]. **(OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].
Bos (Bos, 2010)	(EEG) [-NOISE].	**<u>Red. dim. and red. obj:</u>** <EEG> [PCA]. **(CONV. SINAL)** (EEG) [-NOISE [BPF [FOURIER]]]. **(NORM, AMP, AND FILTER)** (EEG) [-NOISE [BPF]. **(SEC. AND GER. SIGNAL)** (EEG) [-NOISE [BPF [FOURIER [BANDS]]]]. **(OTHER)** {EEGLAB}.
Setz et al. (Setz et al., 2010)	(EDA) [DISCARDDATA, MANADJUST [-NOISE]].	**<u>Red. dim. and red. obj:</u>** <EDA> [WFA]. **(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, LPF [HPF [LPF]]] **(OTHER)** (EDA) [PEAKDETECT].
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE].	**<u>Red. dim. and red. obj:</u>** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS]. **(CONV. SINAL)** (ECG(HR, HRV)) [FOURIER]. **(NORM, AMP, AND FILTER)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	(RESP) [-PEAK].	**<u>Red. dim. and red. obj:</u>** <ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT]. **(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(BALANCING AND LABELING)** (RESP(RR)) <AMP> [LABELING].
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	(PUPIL) [FAKEDATA].	**(NORM, AMP, AND FILTER)** (PUPIL, EDA) [NORM].
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR)) [MANADJUST, FAKEDATA].	**(NORM, AMP, AND FILTER)** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(SAMPLING TECH)**

		(ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
Zhai & Barreto (Zhai & Barreto, 2006)	(PUPIL) <DIAMETER> [-NOISE [FAKEDATA]].	**(NORM, AMP, AND FILTER)** (ST) [SIGAMP [LPF [NORM]]] and (BVP(IBI), EDA) [NORM].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard, Vyzas, & Healey, 2001)	(EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY].	**<u>Red. dim. and red. obj:</u>** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(BALANCING AND LABELING)** (STRESS) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
Herbon et al. (Herbon et al., 2005)	(HR, EDA, PUPIL, EMOTIONS) [DISCARDDATA] and (HR, EDA, PUPIL) <STD <THRESHOLD>> [DISCARDDATA].	**(CONV. SINAL)** (HR, EDA, ST, PUPIL) [ZTRANSFORM].
Partala et al. (Partala et al., 2005)	(EMG) [-EYEBLINK].	**(NORM, AMP, AND FILTER)** (EMG) [SIGAMP [HPF, LPF]]. **(SEC. AND GER. SIGNAL)** (EMG) and (EMOTIONS) [LABELING]. **(OTHER)** (EMG) [TTEST].
Van Eck et al. (van Eck et al., 2005)	(HEALTH) [DISCARDDATA] and (CORT) [-OUTLIERS].	**<u>Red. dim. and red. obj:</u>** (LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH) [PCA [AGGREGATION]]]. **(BALANCING AND LABELING)** (STRESS) [LABELING].
K. H. Kim et al. (K. H. Kim et al., 2004)	(ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]].	**(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT]. **(SAMPLING TECH)** (ECG(HRV), EDA) [DECIMATION]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Partala & Surakka (Partala & Surakka, 2003)	(PUPIL) [DISCARDDATA, -EYEBLINK].	**(BALANCING AND LABELING)** (PUPIL) [LABELING]. **(OTHER)** (PUPIL) [PEAKDETECT, TTEST].

Vrijkotte et al. (Vrijkotte et al., 2000)	(BP(SBP, DBP)) [-NOISE, -OUTLIERS].	**(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]]. **(SAMPLING TECH)** (STRESS) [INTENTIONAL, STRATIFIED]. **(BALANCING AND LABELING)** BP(SBP, DBP) [LABELING]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
L. S. Chen et al. (L. S. Chen et al., 1998)	(EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].	**(CONV. SINAL)** (EYES, MOUTH) [FOURIER]. **(NORM, AMP, AND FILTER)** (PITCH) [NORM]. **(SEC. AND GER. SIGNAL)** (SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX].
Rajita Sinha (Rajita Sinha, 1996)	(BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE].	<u>**Red. dim. and red. obj:**</u> (EMG) [MANSELECT]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM]. **(SAMPLING TECH)** (EMG, ST) [SYSTEMATIC].
Scott R. Vrana (Scott R. Vrana, 1993)	(ECG(HR)) [DISCARDDATA].	**(CONV. SINAL)** (EMOTIONS) [QUALI-QUANTI]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, LPF, HPF].
R Sinha et al. (R Sinha et al., 1992)	(ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA].	<u>**Red. dim. and red. obj:**</u> (BP(SBP, DBP), ECG(HR)) [MANSELECT]. **(NORM, AMP, AND FILTER)** (ECG(HR)) [SIGAMP]. **(SEC. AND GER. SIGNAL)** (ECG) [R-R].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.1.2. Dimensional reduction and object redundancy

This section discusses the problem of attribute and object redundancy. Initially the techniques related to dimensional reduction are presented, which address the problem of the high number of attributes and their redundancy, followed by techniques related to object redundancy.

Even the best-known classification algorithms are sensitive to the presence of irrelevant and redundant attributes in a dataset (Gilad-bachrach, 2004). The high number of attributes is known as the curse of dimensionality (Bellman, 1961) and describes the problem caused by the large growth of the dataset resulting from the introduction of new attributes (Gilad-bachrach, 2004) (Gama et al., 2012) (J. Kim & André, 2008). As increasing the number of attributes exponentially increases the number of possible data combinations, classification algorithms can become inefficient. <u>Dimensional reduction</u> techniques aim to find the attributes that contribute effectively to the success rates of classifiers by evaluating the quality of the correlation between them (Jerritta et al., 2011). Dimensional reduction contributes to decreased processing effort, increased system performance and algorithm hit rates (Raschka, 2014) (J. Kim & Andre, 2008) (Guyon & Elisseeff, 2003) (Mokhayeri & Toosizadeh, 2011).

To discover which redundant attributes exist in a dataset, researchers use pre-processing techniques. In addition to the automatic ones discussed below, researchers use manual tools to analyze the redundancy and relationship between attributes: the scatter plot **[SCATTER]** is a mathematical diagram that allows to visually analyze the patterns formed in the two-dimensional Cartesian space between two variables in order to assess their interdependence (i.e. relationship or redundancy) (e.g. Perdiz et al. (Perdiz et al., 2017)) (Phinyomark, Phukpattaranont, & Limsakul, 2012) (Guyon & Elisseeff, 2003); Bogolomov et al., Sano et al. and LikamWa et al., used correlation techniques **[CORRELATION]** to measure the strength of the relationship between variables (e.g. Person Product-Moment Correlation) (Sigma, 2016) (Andale, 2012) (Crossman, 2017) (W. H. Press, B. P. Flannery, n.d.) (Laerd, 2013) (Bogomolov et al., 2014) (Sano & Picard, 2013b) (LiKamWa et al., 2013); and Chi-square [$\mathbf{X^2}$] is a statistical test that evaluates the dependence between two variables (Cambridge University, 2008) (Adhikari, 2016) (the value of X^2 represents the degree of relevance of a property in the class to which it belongs (Alzoubi et al., 2013)).

However, researchers mainly use automatic techniques to support the process of dimensional reduction. There are several algorithms used by the researchers included in this literature review for this purpose: Principal Component Analysis **[PCA]** is an unsupervised algorithm (i.e. it ignores class labels) that converts a set of possibly correlatable objects into a new dataset of uncorrelated data (Raschka, 2014) (Gama et al., 2012) (Pearson, 1901), and the main goal is to find the main components responsible for the variance of the data (Raschka, 2014); Linear Discriminant Analysis **[LDA]** is a supervised algorithm that aims to design a dataset with fewer dimensions making an optimized separation by classes to avoid overfitting and decrease the processing effort (Raschka, 2014) (Fisher, 1936b) (in addition to finding the variance culprits as PCA does, LDA maximizes the separation between the different classes (Raschka, 2014)) (e.g. Phinyomark et al. used LDA to find the redundant and most representative properties in their dataset (Phinyomark et al., 2012)); Sequential Forward Selection **[SFS]** which performs an in-depth heuristic search on available properties (J. Kim & André, 2008); Sequential Backward Selection **[SBS]** is similar to SFS but does a top-down search (removes a property at each iteration) (J. Kim & André, 2008); Sequential Floating Forward Selection [**SFFS**]. (J. Kim & André, 2008); Genetic Algorithm **[GA]** (J. Kim & André, 2008); Supervised Locality Preserving Projection **[SLPP]** (Turan et al., 2015) (Zheng, Yang, Tan, Jia, & Yang, 2007) (Lu, Lu, Qi, & Wang, 2010); Discriminant-Analysis of Canonical Correlations **[DCC]** (Turan et al., 2015) (T. K. Kim, Kittler, & Cipolla, 2007); Adaboost Algorithm [**ADABOOST**] (Csail, n.d.) (Schapire, 2013) (H. Wang et al., 2010); Best-First Search [**BESTFIRST**] (Mackworth & Goebel, 1998) (Korf, 1993) (Gunes & Piccardi, 2007); Murali et al. created their own feature selection algorithm **[MURALI**] (Murali et al., 2015) (Padmanabhan et al., 2015); Wrapper Feature Selection **[WFS]** (Jaques et al. used WFS to evaluate the relevance of each property in their dataset (Jaques et al., 2015)) (Guyon & Elisseeff, 2003) (Panthong & Srivihok, 2015) (Kohavi & John, 1997); and Fisher's Discriminant Analysis [**FDA**] (Fisher, 1936a) (Fukunaga, 1990) (e.g. Matiko et al. used this algorithm because they consider it robust in dimensional reduction (Matiko et al., 2014)). Some authors also resort to more specific techniques to support dimensional reduction (e.g. Bogomolov et al. selected properties using a scoring system **[BOGOMOLOV]** adapting the Gini Coefficient of Inequality as a metric (Bogomolov et al., 2014)).

Once irrelevant or redundant attributes are discovered, researchers use several strategies to reduce dimensionality: manual selection **[MANSELECT]** of irrelevant attributes to eliminate (e.g. value of an attribute the same across all objects, or personal information of participants), or relevant attributes to consider (process is usually supervised by domain experts and can be aided by visual tools (e.g. SCATTER)) (e.g. Jaques et al. added and removed properties until they achieved a set that allowed them to achieve higher classification accuracy (Jaques et al., 2015)) (this group includes dimensional reduction techniques not identified by the authors (e.g. Basu et al. (Basu et al., 2016), Sinha (Rajita Sinha, 1996), and Sinha et al. (R Sinha et al., 1992)) (Gama et al., 2012); and aggregation **[AGGREGATION]**, i.e. combining several dependent attributes into a single (Gama et al., 2012) (e.g. Phinyomark et al. clustered attributes (EMG) [RAW, NORM] to reduce data redundancy (Phinyomark et al., 2012), van Eck et al. joined several items together to form just the "Positive Affect" and the "Negative Affect" (van Eck et al., 2005)).

Some researchers also address the problem of <u>object redundancy</u>: Gogia et al. removed duplicate collected EEG values from their dataset **[-DUPLICATE**] (Gogia et al., 2016); Sano & Eng. considered only one peak EDA signal object at each time interval **[DISTINCTOBJ]** (i.e. in the same second only one EDA peak was considered) (Sano & Eng, 2016); and Dhall et al. removed redundant VIDEO frames **[-FRAMES]** (Dhall et al., 2011) and Gunes et al. omitted frames with intermediate motion (Gunes & Piccardi, 2007).

RESEARCH	DATASET MAINTENANCE	
	RED. DIM. AND RED. OBJS	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)	(EMG) [SCATTER, LDA [AGGREGATION]].	**(NORM, AMP, AND FILTER)** (EMG) [BPF, SIGAMP, NORM].
Gogia et al. (Gogia et al., 2016)	(EEG) [-DUPLICATE].	<u>**Noise, d. inc. and inc:**</u> (EEG) [-EYEBLINK]. **(BALANCING AND LABELING)** (EEG) [[[-EYEBLINK, -DUPLICATE] [LABELING]] [+ARTIFICIALDATA]].
Z. Zhang et al. (Z. Zhang et al., 2016)	(HEAD, FACS) [PCA].	**(SAMPLING TECH)** (HEAD, FACS) [RANDOM]. **(BALANCING AND LABELING)** (FACS) [LABELING]. (**OTHER)** (FACS) [FINDREGION, SI-SSM]. {ZFACE}.
Sano & Eng (Sano & Eng, 2016)	(EDA) [LPF [DY/DX [DISTINCTOBJ]]].	<u>**Noise, d. inc. and inc:**</u> (EDA) [-NOISE]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING]. (**OTHER)** (ACC) [MOTIONDETECT].
Basu et al. (Basu et al., 2016)	(ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM [MANSELECT]].	**(NORM, AMP, AND FILTER)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM]. (**OTHER)** {KHRV, WEKA, LABCHART, MATLAB, ORIGIN}.
Turan et al. (Turan et al., 2015)	(FACE, EYES) [SLPP, DCC].	**(BALANCING AND LABELING)** (FACE, EYES) [LABELING]. (**OTHER)**

		(EYES) [FINDREGION].
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)	(((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI].	**<u>Noise, d. inc. and inc:</u>** (ECG, ICG) [-NOISE]. **(NORM, AMP, AND FILTER)** (ECG, EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (ECG, ICG) [SIGSPLIT]. (**OTHER)** (ECG) [PEAKDETECT].
Jaques et al. (Jaques et al., 2015)	(EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT].	**<u>Noise, d. inc. and inc:</u>** (EDA) [LPF [NORM [**-PEAK]]]**, (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]] and <ACC> [NORM]. **(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX]. **(BALANCING AND LABELING)** (HAPPY) [LABELING].
Matiko et al. (Matiko et al., 2014)	(EEG) [SCATTER, FDA].	**(NORM, AMP, AND FILTER)** (EDA) [FDA [NORM]]. **(BALANCING AND LABELING)** (EDA) [LABELING].
Bogomolov et al. (Bogomolov et al., 2014)	(PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [CORELATION, BOGOMOLOV [MANSELECT]].	**(NORM, AMP, AND FILTER)** (PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [NORM].
Alzoubi et al. (Alzoubi et al., 2013)	(ECG(HRV), RESP, EDA, EMG) [X^2].	**(BALANCING AND LABELING)** (ECG(HRV), RESP, EDA, EMG) [SPREADSUBSAMPLE]. (**OTHER)** {AUBT}.
Sano & Picard (Sano & Picard, 2013b)	<EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS].	**(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [DY/DX]] and (ACC) [ADL]. (**OTHER)** (EDA) [[LPF [DY/DX [PEAKDETECT]]]].
LikamWa et al. (LiKamWa et al., 2013)	<MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION].	**<u>Noise, d. inc. and inc:</u>** (MOOD) [RELIABILITY, CONSISTENCY]. **(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(SEC. AND GER. SIGNAL)** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING]. (**OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION>

		[HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
C. Y. Chang et al. (Chang et al., 2012)	(ECG, PR, BVP, EDA) [MANSELECT].	**<u>Noise, d. inc. and inc:</u>** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]]. (**OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Dhall et al. (Dhall et al., 2011)	(FACE) [VIDEO-PICS [-FRAMES [PCA]].	**(CONV. SINAL)** (FACE) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (FACE) [VIDEO-PICS [NORM]]. (**OTHER)** (FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	<ECG(HRV), PPG, PUPIL> [GA].	**<u>Noise, d. inc. and inc:</u>** (PUPIL) [-NOISE, -EYEBLINK]. **(CONV. SINAL)** (PUPIL) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (PUPIL) [IMGSIZE, IMGINTENSITY]. **(SEC. AND GER. SIGNAL)** (ECG(HRV)) [BANDS]. (**OTHER)** (PUPIL) [FINDREGION, BLINKDETECT].
H. Wang et al. (H. Wang et al., 2010)	<EYES> [ADABOOST].	**<u>Noise, d. inc. and inc:</u>** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG]. **(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING]. (**OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].
Bos (Bos, 2010)	<EEG> [PCA].	**<u>Noise, d. inc. and inc:</u>** (EEG) [-NOISE]. **(CONV. SINAL)** (EEG) [-NOISE [BPF [FOURIER]]]. **(NORM, AMP, AND FILTER)** (EEG) [-NOISE [BPF]. **(SEC. AND GER. SIGNAL)** (EEG) [-NOISE [BPF [FOURIER [BANDS]]]]. (**OTHER)** {EEGLAB}.
Setz et al. (Setz et al., 2010)	<EDA> [WFA].	**<u>Noise, d. inc. and inc:</u>** (EDA) [DISCARDDATA, MANADJUST [-NOISE]]. **(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, LPF [HPF [LPF]]]

		(**OTHER**) (EDA) [PEAKDETECT].
J. Kim & Andre (J. Kim & André, 2008)	<ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS].	<u>**Noise, d. inc. and inc:**</u> (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(CONV. SINAL)** (ECG(HR, HRV)) [FOURIER]. **(NORM, AMP, AND FILTER)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]]. (**OTHER**) (ECG(HR, HRV)) [PEAKDETECT].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	<ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT].	<u>**Noise, d. inc. and inc:**</u> (RESP) [-PEAK]. **(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(BALANCING AND LABELING)** (RESP(RR)) <AMP> [LABELING].
Gunes & Piccardi (Gunes & Piccardi, 2007)	(SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST].	**(CONV. SINAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY]. **(NORM, AMP, AND FILTER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST]. **(SEC. AND GER. SIGNAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG]. (**OTHER**) (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.
Castellano et al. (Castellano et al., 2007)	(ARMS) [DISCARDDATA].	**(NORM, AMP, AND FILTER)** (ARMS) <MOTION <MAX, MIN>> [NORM]. **(SEC. AND GER. SIGNAL)** (ARMS) [-IMGBKG]. (**OTHER**) {EYESWEB}.
Sebe et al. (Sebe et al., 2006)	(PITCH) [CORRELATION].	**(CONV. SINAL)** (HEAD, EYEBROWS, EYELIDS, MOUTH) [3D2D]. **(SEC. AND GER. SIGNAL)** (HEAD, EYEBROWS, EYELIDS, MOUTH, VOLUME, SPEECH, PITCH) [INTEGRATION].
J. A. Healey & Picard	<EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT].	<u>**Noise, d. inc. and inc:**</u>

(J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)		(EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(BALANCING AND LABELING)** (STRESS) [LABELING]. (**OTHER)** (EDA) [PEAKDETECT].
Van Eck et al. (van Eck et al., 2005)	(LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH) [PCA [AGGREGATION]].	**<u>Noise, d. inc. and inc:</u>** (HEALTH) [DISCARDDATA] and (CORT) [-OUTLIERS]. **(BALANCING AND LABELING)** (STRESS) [LABELING].
Busso et al. (Busso et al., 2004)	<PITCH, VOLUME> [SBS], <FOREHEAD, EYEBROWS, EYES, CHEEKS> [PCA] and <PITCH, VOLUME, FOREHEAD, EYEBROWS, EYES, CHEEKS> [SBS [AGGREGATION], MANSELECT].	(**OTHER)** (FOREHEAD, EYEBROWS, EYES, CHEEKS) [FINDREGION, CLUSTERING].
C J Harmer et al. (C J Harmer et al., 2003)	(MOOD, ENERGY) [PCA].	
Ritz et al. (Ritz et al., 2000)	(BP(SBP)) [CORRELATION].	**(SEC. AND GER. SIGNAL)** (BP(SBP)) [INTERVALSPLIT]. (**OTHER)** (HR, BP(SBP, DBP), ROS, RR, VT, EDA, EMOTIONS) [ANOVA].
Rajita Sinha (Rajita Sinha, 1996)	(EMG) [MANSELECT].	**<u>Noise, d. inc. and inc:</u>** (BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM]. **(SAMPLING TECH)** (EMG, ST) [SYSTEMATIC].
R Sinha et al. (R Sinha et al., 1992)	(BP(SBP, DBP), ECG(HR)) [MANSELECT].	**<u>Noise, d. inc. and inc:</u>** (ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA]. **(NORM, AMP, AND FILTER)** (ECG(HR)) [SIGAMP]. **(SEC. AND GER. SIGNAL)** (ECG) [R-R].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.1.3. Analysis

The performance of algorithms can be affected by the state of the data (Gama et al., 2012). The input data of the pre-processing techniques of emotional detection systems are imperfect, because they are collected from the natural environment (i.e. analog world) (e.g. human body) through sensors that are signal discretizing devices. Several problems can result from such data digitization: noise (e.g. unexpected values); incomplete data (i.e. missing values); inconsistent data (i.e. contradictory values); and redundant data (i.e. values that can be inferred from others) (Jerritta et al., 2011) (Gama et al., 2012). Furthermore, the paradox between the temptation to increase the number of attributes in an attempt to improve hit rates, and the problems caused in algorithms because of high dimensionality (Raschka, 2014) (Gama et al., 2012) (J. Kim & Andre, 2008), for researchers, represents an added concern because of the weighing between pros and cons in the addition of data or properties. The dataset maintenance techniques allow to make it less imperfect by detecting, correcting and mitigating problems. Increasing the quality of the data makes the dataset a better input to machine learning algorithms, promoting the accuracy of the results (K. H. Kim et al., 2004) (Mokhayeri & Toosizadeh, 2011) (Gama et al., 2012).

Transversely, researchers are concerned about the noise of the data collected from the context. The importance of the quality of the input from the systems will be behind this concern. The techniques most used by the authors to solve the problem of incomplete data are DISCARDDATA and the synthetic generation of missing data (i.e. FAKEDATA). Noteworthy, however, are the TOLERANCE and RELIABILITY techniques that admit the margin for human failures and the need for evaluation of the impact of these failures on the dataset.

The concern for data quality is also evident in the evaluation of data CONSISTENCY and in the MITIGATION done of possible signal interferences. Also noteworthy is the large number of researchers who resort to manual data editing (i.e. MANADJUST and MANINSERT), and it is not clear what impact these actions have on the data and on the validity of the results obtained from them.

The authors also resort to dimensional reduction techniques, in order to find the attributes that actually contribute to the hit rates of the classifiers (Jerritta et al., 2011) (Guyon & Elisseeff, 2003) (Gama et al., 2012). More of them use their own algorithms for this purpose than those that use more visual (i.e. less automatic) methods such as SCATTER and CORRELATION. Object redundancy is analyzed in a much more residual way because it will be difficult to define when two objects are really redundant. If the objects present in the dataset result from the discretization of an analog signal, they symbolize different data points that have existed in the natural world, and the claim that they have been repeated can be controversial.

RESEARCH	NOISE, D. INC. AND INC.	RED. DIM. AND RED. OBJS	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)		(EMG) [SCATTER, LDA [AGGREGATION]].	**(NORM, AMP, AND FILTER)** (EMG) [BPF, SIGAMP, NORM].
S. H. Lee et al. (S. H. Lee et al., 2016)	(FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)) [FAKEDATA].		**(NORM, AMP, AND FILTER)** (EYEBROWS, EYELIDS) [NORM]. **(OTHER)** (FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH) [CLUSTERING, SPARSEREP] and (EYEBROWS,

			EYELIDS) [FINDREGION, CROP]. {HAC}.
Gogia et al. (Gogia et al., 2016)	(EEG) [-EYEBLINK].	(EEG) [-DUPLICATE].	**(BALANCING AND LABELING)** (EEG) [[[-EYEBLINK, -DUPLICATE] [LABELING]] [+ARTIFICIALDATA]].
Z. Zhang et al. (Z. Zhang et al., 2016)		(HEAD, FACS) [PCA].	**(SAMPLING TECH)** (HEAD, FACS) [RANDOM]. **(BALANCING AND LABELING)** (FACS) [LABELING]. **(OTHER)** (FACS) [FINDREGION, SI-SSM]. {ZFACE}.
Sano & Eng (Sano & Eng, 2016)	(EDA) [-NOISE].	(EDA) [LPF [DY/DX [DISTINCTOBJ]]].	**(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING]. **(OTHER)** (ACC) [MOTIONDETECT].
Zhao et al. (Zhao et al., 2016)	(RESP, HR) [-NOISE].		**(NORM, AMP, AND FILTER)** (RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF]. **(SEC. AND GER. SIGNAL)** (RESP, HR) [D2Y/DX2, ZHAO2]. **(OTHER)** (RESP) [LPF [PEAKDETECT]].
Zenonos et al. (Zenonos et al., 2016)	(MOOD, EMOTIONS) [TOLERANCE].		**(NORM, AMP, AND FILTER)** (IBI) [NORM]. **(SEC. AND GER. SIGNAL)** (IBI) [BANDS]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING].
Basu et al. (Basu et al., 2016)		(ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM [MANSELECT]].	**(NORM, AMP, AND FILTER)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM]. **(OTHER)** {KHRV, WEKA, LABCHART, MATLAB, ORIGIN}.
Aracena et al. (Aracena et al., 2016)	(PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE].		**(NORM, AMP, AND FILTER)** (PUPIL) [LPF, NORM]. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].
Turan et al. (Turan et al., 2015)		(FACE, EYES) [SLPP, DCC].	**(BALANCING AND LABELING)** (FACE, EYES) [LABELING]. **(OTHER)** (EYES) [FINDREGION].
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)	(ECG, ICG) [-NOISE].	(((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI].	**(NORM, AMP, AND FILTER)** (ECG, EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (ECG, ICG) [SIGSPLIT]. **(OTHER)** (ECG) [PEAKDETECT].
Jaques et al.	(EDA) [LPF [NORM [-**PEAK**]]], (SCREEN)	(EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY,	**(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]] and

(Jaques et al., 2015)	[DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]].	ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT].	<ACC> [NORM]. **(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX]. **(BALANCING AND LABELING)** (HAPPY) [LABELING].
Matiko et al. (Matiko et al., 2014)		(EEG) [SCATTER, FDA].	**(NORM, AMP, AND FILTER)** (EDA) [FDA [NORM]]. **(BALANCING AND LABELING)** (EDA) [LABELING].
Bogomolov et al. (Bogomolov et al., 2014)		(PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [CORELATION, BOGOMOLOV [MANSELECT]].	**(NORM, AMP, AND FILTER)** (PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [NORM].
Soleymani et al. (Soleymani et al., 2013)	(EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE].		**(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING]. **(OTHER)** {FEELTRACE} .
Alzoubi et al. (Alzoubi et al., 2013)		(ECG(HRV), RESP, EDA, EMG) [X^2].	**(BALANCING AND LABELING)** (ECG(HRV), RESP, EDA, EMG) [SPREADSUBSAMPLE]. **(OTHER)** {AUBT}.
Sano & Picard (Sano & Picard, 2013b)		<EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS].	**(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [DY/DX]] and (ACC) [ADL]. **(OTHER)** (EDA) [[LPF [DY/DX [PEAKDETECT]]]].
Kawai et al. (Kawai et al., 2013)	(PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION].		**(CONV. SINAL)** (PUPIL) [BINARY]. **(NORM, AMP, AND FILTER)** (PUPIL) <DIAMETER> [KAWAI2 [NORM]]. **(OTHER)** (PUPIL) [FINDREGION, CLUSTERING, KAWAI1].
Babiker et al.	(PUPIL) [MITIGATION],		**(NORM, AMP, AND FILTER)** <PUPIL> [NORM].

(Babiker et al., 2013)	<PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]].		**(SEC. AND GER. SIGNAL)** (PUPIL) <INTERVALSPLIT>. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC]. **(OTHER)** (PUPIL) [FINDREGION].
LikamWa et al. (LiKamWa et al., 2013)	(MOOD) [RELIABILITY, CONSISTENCY].	<MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION].	**(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(SEC. AND GER. SIGNAL)** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING]. **(OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
C. Y. Chang et al. (Chang et al., 2012)	(ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]].	(ECG, PR, BVP, EDA) [MANSELECT].	**(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Dhall et al. (Dhall et al., 2011)		(FACE) [VIDEO-PICS [-FRAMES [PCA]].	**(CONV. SINAL)** (FACE) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (FACE) [VIDEO-PICS [NORM]]. **(OTHER)** (FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(PUPIL) [-NOISE, -EYEBLINK].	<ECG(HRV), PPG, PUPIL> [GA].	**(CONV. SINAL)** (PUPIL) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (PUPIL) [IMGSIZE, IMGINTENSITY]. **(SEC. AND GER. SIGNAL)** (ECG(HRV)) [BANDS]. **(OTHER)** (PUPIL) [FINDREGION, BLINKDETECT].
Hernandez et al. (Hernandez et al., 2011)	(EDA) [-NOISE].	**(NORM, AMP, AND FILTER)** (EDA, STRESS) [NORM] and <EDA, STRESS> [NORM].	

		(BALANCING AND LABELING) (CALL) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].	
N. Lane et al. (N. Lane et al., 2011)	(SLEEP, PHYSI) [MANINSERT].		**(SEC. AND GER. SIGNAL)** (ACC) [ADL]. **(OTHER)** (SLEEP) [LANE1] and (SLEEP, PHYSI) [MANADJUST].
H. Wang et al. (H. Wang et al., 2010)	(EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]].	<EYES> [ADABOOST].	**(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG]. **(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING]. **(OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].
Bos (Bos, 2010)	(EEG) [-NOISE].	<EEG> [PCA].	**(CONV. SINAL)** (EEG) [-NOISE [BPF [FOURIER]]]. **(NORM, AMP, AND FILTER)** (EEG) [-NOISE [BPF]. **(SEC. AND GER. SIGNAL)** (EEG) [-NOISE [BPF [FOURIER [BANDS]]]]. **(OTHER)** {EEGLAB}.
Setz et al. (Setz et al., 2010)	(EDA) [DISCARDDATA, MANADJUST [-NOISE]].	<EDA> [WFA].	**(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, LPF [HPF [LPF]]] **(OTHER)** (EDA) [PEAKDETECT].
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE].	<ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS].	**(CONV. SINAL)** (ECG(HR, HRV)) [FOURIER]. **(NORM, AMP, AND FILTER)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	(RESP) [-PEAK].	<ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT].	**(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(BALANCING AND LABELING)** (RESP(RR)) <AMP> [LABELING].
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	(PUPIL) [FAKEDATA].		**(NORM, AMP, AND FILTER)** (PUPIL, EDA) [NORM].

Gunes & Piccardi (Gunes & Piccardi, 2007)		(SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST].	**(CONV. SINAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY]. **(NORM, AMP, AND FILTER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST]. **(SEC. AND GER. SIGNAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG]. **(OTHER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.
Castellano et al. (Castellano et al., 2007)		(ARMS) [DISCARDDATA].	**(NORM, AMP, AND FILTER)** (ARMS) <MOTION <MAX, MIN>> [NORM]. **(SEC. AND GER. SIGNAL)** (ARMS) [-IMGBKG]. **(OTHER)** {EYESWEB}.
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR)) [MANADJUST, FAKEDATA].		**(NORM, AMP, AND FILTER)** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(SAMPLING TECH)** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING]. **(OTHER)** (ECG(HR), EDA, EMG) HISTOGRAM].
Sebe et al. (Sebe et al., 2006)		(PITCH) [CORRELATION].	**(CONV. SINAL)** (HEAD, EYEBROWS, EYELIDS, MOUTH) [3D2D]. **(SEC. AND GER. SIGNAL)** (HEAD, EYEBROWS, EYELIDS, MOUTH, VOLUME, SPEECH, PITCH) [INTEGRATION].

Zhai & Barreto (Zhai & Barreto, 2006)	(PUPIL) <DIAMETER>[-NOISE [FAKEDATA]].		**(NORM, AMP, AND FILTER)** (ST) [SIGAMP [LPF [NORM]]] and (BVP(IBI), EDA) [NORM].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	(EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY].	<EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT].	**(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(BALANCING AND LABELING)** (STRESS) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
Herbon et al. (Herbon et al., 2005)	(HR, EDA, PUPIL, EMOTIONS) [DISCARDDATA] and (HR, EDA, PUPIL) <STD <THRESHOLD>> [DISCARDDATA].		**(CONV. SINAL)** (HR, EDA, ST, PUPIL) [ZTRANSFORM].
Partala et al. (Partala et al., 2005)	(EMG) [-EYEBLINK].		**(NORM, AMP, AND FILTER)** (EMG) [SIGAMP [HPF, LPF]]. **(SEC. AND GER. SIGNAL)** (EMG) and (EMOTIONS) [LABELING]. **(OTHER)** (EMG) [TTEST].
Van Eck et al. (van Eck et al., 2005)	(HEALTH) [DISCARDDATA] AND (CORT) [-OUTLIERS].	(LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH) [PCA [AGGREGATION]]].	**(BALANCING AND LABELING)** (STRESS) [LABELING].
Busso et al. (Busso et al., 2004)		<PITCH, VOLUME> [SBS], <FOREHEAD, EYEBROWS, EYES, CHEEKS> [PCA] and <PITCH, VOLUME, FOREHEAD, EYEBROWS, EYES, CHEEKS> [SBS [AGGREGATION], MANSELECT].	**(OTHER)** (FOREHEAD, EYEBROWS, EYES, CHEEKS) [FINDREGION, CLUSTERING].
K. H. Kim et al. (K. H. Kim et al., 2004)	(ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]].		**(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT]. **(SAMPLING TECH)** (ECG(HRV), EDA) [DECIMATION]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].

Partala & Surakka (Partala & Surakka, 2003)	(PUPIL) [DISCARDDATA, -EYEBLINK].		**(BALANCING AND LABELING)** (PUPIL) [LABELING]. **(OTHER)** (PUPIL) [PEAKDETECT, TTEST].
C J Harmer et al. (C J Harmer et al., 2003)		(MOOD, ENERGY) [PCA].	
Vrijkotte et al. (Vrijkotte et al., 2000)	(BP(SBP, DBP)) [-NOISE, -OUTLIERS].		**(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI (RMSSD (VAGAL))), ACC) [INTEGRATION [ADL]]. **(SAMPLING TECH)** (STRESS) [INTENTIONAL, STRATIFIED]. **(BALANCING AND LABELING)** BP(SBP, DBP) [LABELING]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
Ritz et al. (Ritz et al., 2000)		(BP(SBP)) [CORRELATION].	**(SEC. AND GER. SIGNAL)** (BP(SBP)) [INTERVALSPLIT]. **(OTHER)** (HR, BP(SBP, DBP), ROS, RR, VT, EDA, EMOTIONS) [ANOVA].
L. S. Chen et al. (L. S. Chen et al., 1998)	(EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].		**(CONV. SINAL)** (EYES, MOUTH) [FOURIER]. **(NORM, AMP, AND FILTER)** (PITCH] [NORM]. **(SEC. AND GER. SIGNAL)** (SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX].
Rajita Sinha (Rajita Sinha, 1996)	(BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE].	(EMG) [MANSELECT].	**(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM]. **(SAMPLING TECH)** (EMG, ST) [SYSTEMATIC].
Scott R. Vrana (Scott R. Vrana, 1993)	(ECG(HR)) [DISCARDDATA].		**(CONV. SINAL)** (EMOTIONS) [QUALI-QUANTI]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, LPF, HPF].
R Sinha et al. (R Sinha et al., 1992)	(ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA].	(BP(SBP, DBP), ECG(HR)) [MANSELECT].	**(NORM, AMP, AND FILTER)** (ECG(HR)) [SIGAMP]. **(SEC. AND GER. SIGNAL)** (ECG) [R-R].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.2. SIGNAL MAINTENANCE

This section presents pre-processing techniques responsible for fitting the signals to the processing algorithms.

Based on the literature under review, we decided to group the identified techniques into three categories: i) signal and data type conversion; ii) normalization, amplification, and filters; and iii) segmentation and new signal generation.

4.2.1. Signal conversion

Signal conversion is one of the types of techniques used by researchers in signal maintenance. In the literature reviewed, several signal conversion techniques were identified: VIDEO into PICTURES **[VIDEO-PICS]** (e.g. Mokhayeri et al. (Mokhayeri & Toosizadeh, 2011), Singh et al. converted video into frames to analyze body postures (Singh et al., 2015)); converting PICTURES to grayscale **[GREYSCALE]** and binarizing images **[BINARY]** (e.g. Eckert et al. used GREYSCALE and BINARY to apply MORPHOPS on EYES, EYEBROWS and MOUTH (Eckert et al., 2016); and conversion or modeling from two to three dimensions and vice versa **[3D2D**] (Sebe et al., 2006).

There are also several authors who use Fourier transforms **[FOURIER]** to convert the signal from the time domain to the frequency domain (Bracewell, 2014) (S. W. Smith, 2003): Korkmaz et al. used the Fast Fourier Transform to convert the SPEECH signal (Korkmaz & Atasoy, 2015); and Soleymani et al. used the Short Time Fourier Transform to decrease the temporal resolution of the EEG signal (Soleymani et al., 2013). Authors also use other techniques for domain transformation and signal analysis: Herbon et al. used the Z transform **[ZTRANSFORM]** in reducing differences between subjects in their experiment (Wickert, n.d.) (S. W. Smith, 1997) (Herbon et al., 2005); Nawasalkar et al. used the Hilbert-Huang Transform **[HHT]** to decompose the signal to facilitate analysis in the time-frequency-transform domains (N. E. Huang & Wu, 2008) (Tan, 2016); and Liu et al. used the Fractal Dimension **[FD]** algorithm to extract properties of the EEG signal (Maragos & Sun, 1993) (Theiler, 1990) (Y. Liu et al., 2010).

Also included in this section are techniques related to data type conversion (e.g. Liu et al. converted the LEVELs of the two-dimensional valence/arousal space into discrete emotions by defining a THRESHOLD for each **[2D-DISCRETE**] (Y. Liu et al., 2010.)). Transforming data types of an attribute may be necessary for several reasons, including the fact that the new type is more suitable for use in a particular algorithm (Gama et al., 2012). Some algorithms only process with numerical value attributes (e.g. Artifitial Neural Networks (ANN), Support Vector Machine (SVM), etc.), and others are better suited to work with qualitative values as in Bayesian models (Gama et al., 2012) (e.g. Vrana converted qualitative to quantitative values **[QUALI-QUANTI]** for a scale of [0;20] (Scott R. Vrana, 1993)).

RESEARCH	SIGNAL MAINTENANCE	
	CONV. SIGNAL	OTHER
Eckert et al. (Eckert et al., 2016)	(EYES, EYEBROWS, NOSE, MOUTH) [GREYSCALE [BINARY]].	**Norm, amp and filter:** (EYES, EYEBROWS, NOSE, MOUTH) [IMGCONTRAST]. **(OTHER)** EYES, EYEBROWS, NOSE, MOUTH) [FINDREGION, [GREYSCALE [BINARY [MORPHOPS]]] and (FACS, CAU) [MOTIONDETECT].
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	(SPPECH) [FOURIER].	**Norm, amp and filter:** (SPPECH) [SIGAMP]. **Signal sec. and gest:** (SPEECH) [[FOURIER, SIGAMP] [INTERVALSPLIT, DY/DX, D Y/DX^{22}]].

Singh et al. (Singh et al., 2015)	(SHOULDERS, HANDS) [VIDEO-PICS].	<u>**Signal sec. and gest:**</u> (SHOULDERS, HANDS) [VIDEO-PICS [-IMGBKG]].
Saha et al. (Saha et al., 2014)	(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [VIDEO-PICS].	<u>**Signal sec. and gest:**</u> (HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [-IMGBKG].
Agrawal et al. (Agrawal et al., 2013)	(EYES, MOUTH, LIPS, SKIN) [VIDEO-PICS].	**(OTHER)** (SKIN, EYES, MOUTH) [FINDREGION]. {MATLAB}.
Soleymani et al. (Soleymani et al., 2013)	(EEG) [FOURIER].	<u>**Norm, amp and filter:**</u> (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. <u>**Signal sec. and gest:**</u> (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING]. **(OTHER)** {FEELTRACE}.
Vermun et al. (Vermun et al., 2013)	(HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP and KNEES) [VIDEO-PICS].	
Nawasalkar et al. (Nawasalkar et al., 2013)	(NIBP, RESP(RR)) [HHT].	
Raudonis (Raudonis, 2013)	(PUPIL) [GREYSCALE].	**(OTHER)** (PUPIL) [FINDREGION, RAUDONIS2].
Kawai et al. (Kawai et al., 2013)	(PUPIL) [BINARY].	<u>**Norm, amp and filter:**</u> (PUPIL) <DIAMETER> [KAWAI2 [NORM]]. **(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION]. **(OTHER)** (PUPIL) [FINDREGION, CLUSTERING, KAWAI1].
Yang & Bhanu (S. Yang & Bhanu, 2011)	(HEAD, FACE) [VIDEO-PICS].	<u>**Norm, amp and filter:**</u> (HEAD, FACE) [VIDEO-PICS [IMGALIGN]]. **(OTHER)** (HEAD, FACE) [FINDREGION, YANG1].
Dhall et al. (Dhall et al., 2011)	(FACE) [VIDEO-PICS].	<u>**Norm, amp and filter:**</u> (FACE) [VIDEO-PICS [NORM]]. **(RED. DIM. AND RED. OBJS.)** (FACE) [VIDEO-PICS [-FRAMES [PCA]]. **(OTHER)** (FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].

Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(PUPIL) [VIDEO-PICS].	**<u>Norm, amp and filter:</u>** (PUPIL) [IMGSIZE, IMGINTENSITY]. **<u>Signal sec. and gest:</u>** (ECG(HRV)) [BANDS]. **(NOISE, D. INC. AND INC.)** (PUPIL) [-NOISE, -EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HRV), PPG, PUPIL> [GA]. **(OTHER)** (PUPIL) [FINDREGION, BLINKDETECT].
Bos (Bos, 2010)	(EEG) [-NOISE [BPF [FOURIER]]].	**<u>Norm, amp and filter:</u>** (EEG) [-NOISE [BPF]. **<u>Signal sec. and gest:</u>** (EEG) [-NOISE [BPF [FOURIER [BANDS]]]]. **(NOISE, D. INC. AND INC.)** (EEG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <EEG> [PCA]. **(OTHER)** {EEGLAB}.
Y. Liu et al. (Y. Liu et al., 2010)	(EEG) [FD] and [EMOTIONS] [2D-DISCRETE].	**<u>Norm, amp and filter:</u>** <EEG> [GMP]. **<u>Signal sec. and gest:</u>** <EEG> [INTERVALSPLIT].
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV)) [FOURIER].	**<u>Norm, amp and filter:</u>** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **<u>Signal sec. and gest:</u>** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]]. **(NOISE, D. INC. AND INC.)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Gunes & Piccardi (Gunes & Piccardi, 2007)	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY].	**<u>Norm, amp and filter:</u>** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST]. **<u>Signal sec. and gest:</u>** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG]. **(RED. DIM. AND RED. OBJS.)** (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST]. **(OTHER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS,

		FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.
Sebe et al. (Sebe et al., 2006)	(HEAD, EYEBROWS, EYELIDS, MOUTH) [3D2D].	<u>**Signal sec. and gest:**</u> (HEAD, EYEBROWS, EYELIDS, MOUTH, VOLUME, SPEECH, PITCH) [INTEGRATION]. **(RED. DIM. AND RED. OBJS.)** (PITCH) [CORRELATION].
Herbon et al. (Herbon et al., 2005)	(HR, EDA, ST, PUPIL) [ZTRANSFORM].	**(NOISE, D. INC. AND INC.)** (HR, EDA, PUPIL, EMOTIONS) [DISCARDDATA] and (HR, EDA, PUPIL) <STD <THRESHOLD>> [DISCARDDATA].
Nwe et al. (Nwe et al., 2001)	(SPEECH) [FOURIER].	<u>**Norm, amp and filter:**</u> (SPEECH) [SIGSMOOTH]. <u>**Signal sec. and gest:**</u> (SPEECH) [INTERVALSPLIT].
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	(RESP) [FOURIER].	<u>**Norm, amp and filter:**</u> (PPG(BVP(HR)), ECG(HR, HRV), RESP, EDA) [SIGSMOOTH, NORM]. **(BALANCING AND LABELING)** (EMG) [LABELING]. **(OTHER)** {MATLAB}.
L. S. Chen et al. (L. S. Chen et al., 1998)	(EYES, MOUTH) [FOURIER].	<u>**Norm, amp and filter:**</u> (PITCH) [NORM]. <u>**Signal sec. and gest:**</u> (SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX]. **(NOISE, D. INC. AND INC.)** (EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].
Scott R. Vrana (Scott R. Vrana, 1993)	(EMOTIONS) [QUALI-QUANTI].	<u>**Norm, amp and filter:**</u> (EMG) [SIGAMP, LPF, HPF]. **(NOISE, D. INC. AND INC.)** (ECG(HR)) [DISCARDDATA].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.2.2. Normalization, amplification and filters

<u>Normalization</u> **[NORM]** is used in several contexts: rescaling amplitudes of numerical attributes (e.g. Basu et al. (Basu et al., 2016)); prepare data for the execution of an algorithm or type of algorithm; standardize units of measurement; standardize boundaries between attributes (e.g. to prevent algorithms from considering those with higher values more important) (Gama et al., 2012); etc. However, normalization can also happen at the level of VIDEO, AUDIO and PICTURES: size **[IMGSIZE]** (e.g. Mokhayeri et al. used IMGSIZE to normalize the size of PUPIL images); contrast **[IMGCONTRAST]** (e.g. Eckert et al. improved the contrast of images collected in difficult light environments through a histogram equalization (Eckert et al., 2016)); light intensity **[IMGINTENSITY]** (e.g. Mokhayeri et al. normalized the light intensity of images from PUPIL (Mokhayeri & Toosizadeh, 2011)); Yang et al. used the Sift Flow Algorithm (SIFT**)** (C. Liu, Yuen, & Torralba, 2015) to normalize the alignment **[IMGALIGN]** of faces in images to facilitate generalization of faces in Emotion Avatar Image (EAI) (S. Yang & Bhanu, 2011); and Kawai et al.

used moving average to smooth the diameter of the PUPIL over time **[KAWAI2**] (Kawai et al., 2013).

This literature review also identified techniques related to amplification **[SIGAMP]** and signal filters: Low-Pass Filter **[LPF]** (e.g. Jaques et al. (Jaques et al., 2015)); High-Pass Filter **[HPF]**; Band-Pass Filter **[BPF]** (e.g. Perdiz et al. (Perdiz et al., 2017), Chang et al. (Chang et al., 2012)); and Adaptive Band-pass Filter **[ABPF] (**e.g. Kim et al. (J. Kim & Andre, 2008)).

Also included in this section are other techniques for signal manipulation: Zhao et al. attenuated the effect of the thoracic motion of breathing on the reflected RF signal in order to emphasize the signal and extract the heartbeats **[ZHAO1**] (Zhao et al., 2016); and Mandryk et al. used signal smoothing **[SIGSMOOTH]** of HR after FAKEDATA ageration (i.e. generation of additional data through interpolation to match frequency with EMG and EDA) (Mandryk & Atkins, 2007).

RESEARCH	SIGNAL MAINTENANCE	
	NORM, AMP AND FILTER	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)	(EMG) [BPF, SIGAMP, NORM].	**(RED. DIM. AND RED. OBJS.)** (EMG) [SCATTER, LDA [AGGREGATION]].
S. H. Lee et al. (S. H. Lee et al., 2016)	(EYEBROWS, EYELIDS) [NORM].	**(NOISE, D. INC. AND INC.)** (FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)) [FAKEDATA]. **(OTHER)** (FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH) [CLUSTERING, SPARSEREP] and (EYEBROWS, EYELIDS) [FINDREGION, CROP]. {HAC}.
Eckert et al. (Eckert et al., 2016)	(EYES, EYEBROWS, NOSE, MOUTH) [IMGCONTRAST].	**Conv. sign:** (EYES, EYEBROWS, NOSE, MOUTH) [GREYSCALE [BINARY]]. **(OTHER)** EYES, EYEBROWS, NOSE, MOUTH) [FINDREGION, [GREYSCALE [BINARY [MORPHOPS]]] and (FACS, CAU) [MOTIONDETECT].
Sano & Eng (Sano & Eng, 2016)	(EDA) [LPF [NORM]].	**Signal sec. and gest:** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING]. **(OTHER)** (ACC) [MOTIONDETECT].
Zhao et al. (Zhao et al., 2016)	(RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF].	**Signal sec. and gest:** (RESP, HR) [D2Y/DX2, ZHAO2]. **(NOISE, D. INC. AND INC.)** (RESP, HR) [-NOISE]. **(OTHER)** (RESP) [LPF [PEAKDETECT]].
Zenonos et al.	(IBI) [NORM].	**Signal sec. and gest:**

(Zenonos et al., 2016)		(IBI) [BANDS]. **(NOISE, D. INC. AND INC.)** (MOOD, EMOTIONS) [TOLERANCE]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING].
Basu et al. (Basu et al., 2016)	(ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM].	**(RED. DIM. AND RED. OBJS.)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM [MANSELECT]]. **(OTHER)** {KHRV, WEKA, LABCHART, MATLAB, ORIGIN}.
Aracena et al. (Aracena et al., 2016)	(PUPIL) [LPF, NORM].	**(NOISE, D. INC. AND INC.)** (PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE]. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].
Adams & Robinson (Adams & Robinson, 2015)	(FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)) [NORM].	**(OTHER)** (GAZE) [FINDREGION].
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	(SPPECH) [SIGAMP].	<u>**Conv. sign:**</u> (SPPECH) [FOURIER]. <u>**Signal sec. and gest:**</u> (SPEECH) [[FOURIER, SIGAMP] [INTERVALSPLIT, DY/DX, D Y/DX^{22}]].
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)	(ECG, EDA) [LPF].	<u>**Signal sec. and gest:**</u> (ECG, ICG) [SIGSPLIT]. **(NOISE, D. INC. AND INC.)** (ECG, ICG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI]. **(OTHER)** (ECG) [PEAKDETECT].
Jaques et al. (Jaques et al., 2015)	(EDA) [LPF [NORM]] and <ACC> [NORM].	<u>**Signal sec. and gest:**</u> (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX]. **(NOISE, D. INC. AND INC.)** (EDA) [LPF [NORM [**-PEAK]]]**, (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(RED. DIM. AND RED. OBJS.)** (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT]. **(BALANCING AND LABELING)** (HAPPY) [LABELING].
Cruz et al. (Cruz et al., 2015)	(EOG) [GMP].	<u>**Signal sec. and gest:**</u> (EOG) [INTERVALSPLIT].
Matiko et al. (Matiko et al., 2014)	(EDA) [FDA [NORM]].	**(RED. DIM. AND RED. OBJS.)** (EEG) [SCATTER, FDA]. **(BALANCING AND LABELING)** (EDA) [LABELING].
Bogomolov et al.	(PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [NORM].	**(RED. DIM. AND RED. OBJS.)**

(Bogomolov et al., 2014)		(PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [CORELATION, BOGOMOLOV [MANSELECT]].
Soleymani et al. (Soleymani et al., 2013)	(HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM].	**Conv. sign:** (EEG) [FOURIER]. **Signal sec. and gest:** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING]. **(OTHER)** {FEELTRACE}.
Sano & Picard (Sano & Picard, 2013b)	(EDA) [LPF].	**Signal sec. and gest:** (EDA) [LPF [DY/DX]] and (ACC) [ADL]. **(RED. DIM. AND RED. OBJS.)** <EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS]. **(OTHER)** (EDA) [[LPF [DY/DX [PEAKDETECT]]]].
Kawai et al. (Kawai et al., 2013)	(PUPIL) <DIAMETER> [KAWAI2 [NORM]].	**Conv. sign:** (PUPIL) [BINARY]. **(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION]. **(OTHER)** (PUPIL) [FINDREGION, CLUSTERING, KAWAI1].
Babiker et al. (Babiker et al., 2013)	<PUPIL> [NORM].	**Signal sec. and gest:** (PUPIL) <INTERVALSPLIT>. **(NOISE, D. INC. AND INC.)** (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]]]. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC]. **(OTHER)** (PUPIL) [FINDREGION].
LikamWa et al. (LiKamWa et al., 2013)	(CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM].	**Signal sec. and gest:** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING].

		(OTHER) (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
C. Y. Chang et al. (Chang et al., 2012)	(ECG, PR, BVP, EDA) [LPF, HPF, NORM].	<u>**Signal sec. and gest:**</u> (ECG, PR, BVP, EDA) [R-R]. **(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Yang & Bhanu (S. Yang & Bhanu, 2011)	(HEAD, FACE) [VIDEO-PICS [IMGALIGN]].	<u>**Conv. sign:**</u> (HEAD, FACE) [VIDEO-PICS]. **(OTHER)** (HEAD, FACE) [FINDREGION, YANG1].
Dhall et al. (Dhall et al., 2011)	(FACE) [VIDEO-PICS [NORM]].	<u>**Conv. sign:**</u> (FACE) [VIDEO-PICS]. **(RED. DIM. AND RED. OBJS.)** (FACE) [VIDEO-PICS [-FRAMES [PCA]]. **(OTHER)** (FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(PUPIL) [IMGSIZE, IMGINTENSITY].	<u>**Conv. sign:**</u> (PUPIL) [VIDEO-PICS]. <u>**Signal sec. and gest:**</u> (ECG(HRV)) [BANDS]. **(NOISE, D. INC. AND INC.)** (PUPIL) [-NOISE, -EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HRV), PPG, PUPIL> [GA]. **(OTHER)** (PUPIL) [FINDREGION, BLINKDETECT].
Hernandez et al. (Hernandez et al., 2011)	(EDA, STRESS) [NORM] and <EDA, STRESS> [NORM].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(BALANCING AND LABELING)** (CALL) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
H. Wang et al. (H. Wang et al., 2010)	(EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]].	<u>**Signal sec. and gest:**</u> (EYES) [-IMGBKG]. **(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST]. **(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING]. **(OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].

Bos (Bos, 2010)	(EEG) [-NOISE [BPF].	<u>**Conv. sign:**</u> (EEG) [-NOISE [BPF [FOURIER]]]. <u>**Signal sec. and gest:**</u> (EEG) [-NOISE [BPF [FOURIER [BANDS]]]]. **(NOISE, D. INC. AND INC.)** (EEG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <EEG> [PCA]. **(OTHER)** {EEGLAB}.
Y. Liu et al. (Y. Liu et al., 2010)	<EEG> [GMP].	<u>**Conv. sign:**</u> (EEG) [FD] and [EMOTIONS] [2D-DISCRETE]. <u>**Signal sec. and gest:**</u> <EEG> [INTERVALSPLIT].
Setz et al. (Setz et al., 2010)	(EDA) [SIGAMP, LPF [HPF [LPF]]]	**(NOISE, D. INC. AND INC.)** (EDA) [DISCARDDATA, MANADJUST [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** <EDA> [WFA]. **(OTHER)** (EDA) [PEAKDETECT].
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM].	<u>**Conv. sign:**</u> (ECG(HR, HRV)) [FOURIER]. <u>**Signal sec. and gest:**</u> (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]]. **(NOISE, D. INC. AND INC.)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	(EDA) [LPF].	**(NOISE, D. INC. AND INC.)** (RESP) [-PEAK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT]. **(BALANCING AND LABELING)** (RESP(RR)) <AMP> [LABELING].
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	(PUPIL, EDA) [NORM].	**(NOISE, D. INC. AND INC.)** (PUPIL) [FAKEDATA].
Gunes & Piccardi (Gunes & Piccardi, 2007)	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST].	<u>**Conv. sign:**</u> (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY]. <u>**Signal sec. and gest:**</u> (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG].

		(RED. DIM. AND RED. OBJS.) (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST]. **(OTHER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.
Castellano et al. (Castellano et al., 2007)	(ARMS) <MOTION <MAX, MIN>> [NORM].	<u>**Signal sec. and gest:**</u> (ARMS) [-IMGBKG]. **(RED. DIM. AND RED. OBJS.)** (ARMS) [DISCARDDATA]. **(OTHER)** {EYESWEB}.
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]].	<u>**Signal sec. and gest:**</u> (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA]. **(SAMPLING TECH)** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
Zhai & Barreto (Zhai & Barreto, 2006)	(ST) [SIGAMP [LPF [NORM]]] and (BVP(IBI), EDA) [NORM].	**(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER>[-NOISE [FAKEDATA]].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	(STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH].	<u>**Signal sec. and gest:**</u> (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(BALANCING AND LABELING)** (STRESS) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
Partala et al. (Partala et al., 2005)	(EMG) [SIGAMP [HPF, LPF]].	<u>**Signal sec. and gest:**</u> (EMG) and (EMOTIONS) [LABELING]. **(NOISE, D. INC. AND INC.)** (EMG) [-EYEBLINK]. **(OTHER)** (EMG) [TTEST].
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	(HR, EDA, ST) [NORM].	

K. H. Kim et al. (K. H. Kim et al., 2004)	(EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH].	<u>**Signal sec. and gest:**</u> (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] E (EDA) [INTERVALSPLIT]. **(NOISE, D. INC. AND INC.)** (ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]]. **(SAMPLING TECH)** (ECG(HRV), EDA) [DECIMATION]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Haag et al. (Haag et al., 2004)	(ECG(HR)) [LPF [HPF]], (ECG(HR)) [[DY/DX, D2Y/DX2] [SIGSMOOTH]], (EDA) [NORM [LPF]], (EMG) SIGSMOOTH] and <PPG(BVP(HR)), ECG, RESP, EDA, ST, EMG> [NORM].	<u>**Signal sec. and gest:**</u> (ECG(HR)) [DY/DX, D2Y/DX2] and (PPF(BVP(HR)), RESP) [INTERVALSPLIT]. **(OTHER)** (PPG(BVP(HR))) [HISTOGRAM].
Nwe et al. (Nwe et al., 2001)	(SPEECH) [SIGSMOOTH].	<u>**Conv. sign:**</u> (SPEECH) [FOURIER]. <u>**Signal sec. and gest:**</u> (SPEECH) [INTERVALSPLIT].
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	(PPG(BVP(HR)), ECG(HR, HRV), RESP, EDA) [SIGSMOOTH, NORM].	<u>**Conv. sign:**</u> (RESP) [FOURIER]. **(BALANCING AND LABELING)** (EMG) [LABELING]. **(OTHER)** {MATLAB}.
L. S. Chen et al. (L. S. Chen et al., 1998)	(PITCH] [NORM].	<u>**Conv. sign:**</u> (EYES, MOUTH) [FOURIER]. <u>**Signal sec. and gest:**</u> (SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX]. **(NOISE, D. INC. AND INC.)** (EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].
J. Healey & Picard (J. Healey & Picard, 1998)	(RESP) [NORM], <RESP> [NORM and (EDA) [SIGSMOOTH, NORM].	**(BALANCING AND LABELING)** (EMG, EDA, PPG(BVP(HR)), RESP) [LABELING].
Rajita Sinha (Rajita Sinha, 1996)	(EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM].	**(NOISE, D. INC. AND INC.)** (BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EMG) [MANSELECT]. **(SAMPLING TECH)** (EMG, ST) [SYSTEMATIC].
Scott R. Vrana (Scott R. Vrana, 1993)	(EMG) [SIGAMP, LPF, HPF].	<u>**Conv. sign:**</u> (EMOTIONS) [QUALI-QUANTI]. **(NOISE, D. INC. AND INC.)** (ECG(HR)) [DISCARDDATA].
R Sinha et al. (R Sinha et al., 1992)	(ECG(HR)) [SIGAMP].	<u>**Signal sec. and gest:**</u> (ECG) [R-R]. **(NOISE, D. INC. AND INC.)**

		(ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA]. **(RED. DIM. AND RED. OBJS.)** (BP(SBP, DBP), ECG(HR)) [MANSELECT].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.2.3. Segmentation and new signal generation

This section includes segmentation and signal generation techniques. Segmentation techniques can be seen as generating new signal. However, we decided to separate from this group those techniques whose sole purpose is only signal generation. Thus, in the category of signal segmentation we include the techniques whose main function is to segment the signal, and in the category of new signal generation we include the techniques that only generate new signal.

Several authors have been identified who make use of signal segmentation techniques: Matlovic et al. used the Discrete Wavelet Transform **[DWT]** to extract the ALPHA and BETA waves from EEG [RAW] (Matlovic et al., 2016.)); Zhao et al. segmented the acceleration signal to extract heartbeats from the WiFi signal using a segmentation technique based on variance analysis (VAR) between signal segments **[ZHAO2**] (Zhao et al., 2016); Singh et al. removed the background from images leaving only the straight lines representing the slope of people's shoulders **[-IMGBKG**] (Singh et al., 2015); Gunes et al. segmented skin color based on the HSV (hue, saturation, and value) color space **[COLORSEG**] (Gunes & Piccardi, 2007); Zenonos et al. segmented the power spectral density (PSD) of IBI into bands as a function of intensity (cf. VLF, LF, and HF) **[BANDS]**, Murad & Malkawi also separated various signals (e.g. SV, SBP, DBP, HRV, PEP, etc.) (Murad & Malkawi, 2012), and Soleymani et al. also segmented the EEG signal into several bands (cf. THETA, ALPHA, BETA, and GAMMA) (Soleymani et al., 2013); Korkmaz et al. and Chen et al. divided the SPEECH into several small intervals **[INTERVALSPLIT]** as they were more suitable for MFCC extraction (Korkmaz & Atasoy, 2015) (L. S. Chen et al., 1998), Liu et al. divided the collected EEG signal into several time intervals for use in parallel experiments (Y. Liu et al., 2010), and Kim et al. segmented the various signals collected at various time intervals (J. Kim & Andre, 2008); Murali et al. separated the ECG signal from the ICG signal in order to remove noise from muscle activity **[SIGSPLIT**] (Murali et al., 2015). Also included in this section are specific signal segmentation techniques: Chang et al. used segmented physiological signals into R-R intervals **[R-R**] (Chang et al., 2012); and Kim et al. segmented the ECG in (Normal-to-Normal) intervals **[N-N]** in obtaining the HRV (J. Kim & André, 2008).

Another strategy followed by researchers involves generating new signal based on the original dataset: signal differentiation on the first and second derivative **[DY/DX] [D^{2}Y/DX]^2** (e.g. Jaques et al. calculated the DY/DX of EDA (Jaques et al., 2015)); creating representative data of regularly traveled paths **[PATHSTAKEN]** (e.g. Jaques et al. used the Gaussian Mixture Model (GMM) to calculate regularly traveled paths based on LOCAL data (Jaques et al., 2015)); Kusserow et al. used ACC segmentation to detect jumps and jump phases of ski jumpers **[TASKSPLIT**] (Kusserow et al., 2013); Bauer et al. used the k-means pattern classification algorithm (Duda, Hart, & Stork, 2001) to detect the movement and stopping patterns of participants, in order to characterize the geographic locations commonly frequented by people **[USUALPLACES]** (Bauer & Lukowicz, 2012); and generation of data about daily activities **[ADL]** (e.g. Sano & Eng. used algorithms such as standard zero-crossing detection (Ismailoglu & Yalcin, 1999) (Kosaka, Tanahashi, Matsui, & Fujitsuna, 2002) and Cole function (Cole, Kripke, Gruen, Mullaney, & Gillin, 1992) to detect sleep and awake state, and daily activities such as sitting, running, or walking (Sano & Eng, 2016), Vrijkotte et al. integrated physiological data with PHYSI in order to discriminate body states: lying, sitting, walking, housework, desk work, lunch or dinner, etc.(Vrijkotte et al.)).

Also included in this section are other integration or fusion techniques **[INTEGRATION]** that also generate new data by combining information from various sources or systems (Gama et al., 2012): Jaques et al. integrated GPS coordinates, with WiFi and cell phone data (operator antennas) to create a unique user location record (Jaques et al., 2015); Soleymani et al. merged data from multiple modalities into a single dataset (Soleymani et al., 2013); and Mandryk et al. merged VIDEO, physiological context data, game sound and ambient sound, into a single VIDEO, with the objective to study the emotional component in game environment (Mandryk & Atkins, 2007).

RESEARCH	SIGNAL MAINTENANCE	
	SEC. E GER. SINAL	OTHER
Matlovic et al. (Matlovic et al., 2016)	(EEG) [DWT].	
Sano & Eng (Sano & Eng, 2016)	(EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]].	<u>**Norm, amp and filter:**</u> (EDA) [LPF [NORM]]. **(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING]. **(OTHER)** (ACC) [MOTIONDETECT].
Zhao et al. (Zhao et al., 2016)	(RESP, HR) [D^2Y/DX^2, ZHAO2].	<u>**Norm, amp and filter:**</u> (RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF]. **(NOISE, D. INC. AND INC.)** (RESP, HR) [-NOISE]. **(OTHER)** (RESP) [LPF [PEAKDETECT]].
Zenonos et al. (Zenonos et al., 2016)	(IBI) [BANDS].	<u>**Norm, amp and filter:**</u> (IBI) [NORM]. **(NOISE, D. INC. AND INC.)** (MOOD, EMOTIONS) [TOLERANCE]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING].
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	(SPEECH) [[FOURIER, SIGAMP] [INTERVALSPLIT, DY/DX, D^2Y/DX^2].	<u>**Conv. sign:**</u> (SPPECH) [FOURIER]. <u>**Norm, amp and filter:**</u> (SPPECH) [SIGAMP].
Lalitha et al. (Lalitha et al., 2015)	(SPEECH) [DWT].	
Singh et al. (Singh et al., 2015)	(SHOULDERS, HANDS) [VIDEO-PICS [-IMGBKG]].	<u>**Conv. sign:**</u> (SHOULDERS, HANDS) [VIDEO-PICS].
Murali et al.	(ECG, ICG) [SIGSPLIT].	<u>**Norm, amp and filter:**</u>

(Murali et al., 2015) e (Padmanabhan et al., 2015)		(ECG, EDA) [LPF]. **(NOISE, D. INC. AND INC.)** (ECG, ICG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI]. **(OTHER)** (ECG) [PEAKDETECT].
Jaques et al. (Jaques et al., 2015)	(LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX].	**<u>Norm, amp and filter:</u>** (EDA) [LPF [NORM]] and <ACC> [NORM]. **(NOISE, D. INC. AND INC.)** (EDA) [LPF [NORM [**-PEAK]]]**, (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(RED. DIM. AND RED. OBJS.)** (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT]. **(BALANCING AND LABELING)** (HAPPY) [LABELING].
Cruz et al. (Cruz et al., 2015)	(EOG) [INTERVALSPLIT].	**<u>Norm, amp and filter:</u>** (EOG) [GMP].
Saha et al. (Saha et al., 2014)	(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [-IMGBKG].	**<u>Conv. sign:</u>** (HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [VIDEO-PICS].
Soleymani et al. (Soleymani et al., 2013)	(EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION].	**<u>Conv. sign:</u>** (EEG) [FOURIER]. **<u>Norm, amp and filter:</u>** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING]. **(OTHER)** {FEELTRACE}.
Kusserow et al. (Kusserow et al., 2013)	(ACC) [TASKSPLIT] and (HR, ACC) [INTEGRATION].	
Sano & Picard (Sano & Picard, 2013b)	(EDA) [LPF [DY/DX]] and (ACC) [ADL].	**<u>Norm, amp and filter:</u>** (EDA) [LPF]. **(RED. DIM. AND RED. OBJS.)** <EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS]. **(OTHER)** (EDA) [[LPF [DY/DX [PEAKDETECT]]]].
Babiker et al. (Babiker et al., 2013)	(PUPIL) <INTERVALSPLIT>.	**<u>Norm, amp and filter:</u>** <PUPIL> [NORM].

		(NOISE, D. INC. AND INC.) (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]]]. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC]. **(OTHER)** (PUPIL) [FINDREGION].
LikamWa et al. (LiKamWa et al., 2013)	(MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]].	**Norm, amp and filter:** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING]. **(OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
Murad & Malkawi (Murad & Malkawi, 2012)	(EEG, HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS].	**(BALANCING AND LABELING)** (HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS [LABELING]].
C. Y. Chang et al. (Chang et al., 2012)	(ECG, PR, BVP, EDA) [R-R].	**Norm, amp and filter:** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Bauer & Lukowicz (Bauer & Lukowicz, 2012)	(LOCAL) [INTEGRATION, USUALPLACES].	
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(ECG(HRV)) [BANDS].	**Conv. sign:** (PUPIL) [VIDEO-PICS]. **Norm, amp and filter:** (PUPIL) [IMGSIZE, IMGINTENSITY]. **(NOISE, D. INC. AND INC.)** (PUPIL) [-NOISE, -EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HRV), PPG, PUPIL> [GA]. **(OTHER)** (PUPIL) [FINDREGION, BLINKDETECT].
N. Lane et al. (N. Lane et al., 2011)	(ACC) [ADL].	**(NOISE, D. INC. AND INC.)** (SLEEP, PHYSI) [MANINSERT]. **(OTHER)** (SLEEP) [LANE1] and (SLEEP, PHYSI) [MANADJUST].

H. Wang et al. (H. Wang et al., 2010)	(EYES) [-IMGBKG].	<u>**Norm, amp and filter:**</u> (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST]. **(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING]. **(OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].
Bos (Bos, 2010)	(EEG) [-NOISE [BPF [FOURIER [BANDS]]]].	<u>**Conv. sign:**</u> (EEG) [-NOISE [BPF [FOURIER]]]. <u>**Norm, amp and filter:**</u> (EEG) [-NOISE [BPF]. **(NOISE, D. INC. AND INC.)** (EEG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <EEG> [PCA]. **(OTHER)** {EEGLAB}.
Y. Liu et al. (Y. Liu et al., 2010)	<EEG> [INTERVALSPLIT].	<u>**Conv. sign:**</u> (EEG) [FD] and [EMOTIONS] [2D-DISCRETE]. <u>**Norm, amp and filter:**</u> <EEG> [GMP].
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D^2Y/DX^2]].	<u>**Conv. sign:**</u> (ECG(HR, HRV)) [FOURIER]. <u>**Norm, amp and filter:**</u> (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **(NOISE, D. INC. AND INC.)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Gunes & Piccardi (Gunes & Piccardi, 2007)	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG].	<u>**Conv. sign:**</u> (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY]. <u>**Norm, amp and filter:**</u> (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST]. **(RED. DIM. AND RED. OBJS.)** (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST]. **(OTHER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS,

		FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.
Castellano et al. (Castellano et al., 2007)	(ARMS) [-IMGBKG].	**Norm, amp and filter:** (ARMS) <MOTION <MAX, MIN>> [NORM]. **(RED. DIM. AND RED. OBJS.)** (ARMS) [DISCARDDATA]. **(OTHER)** {EYESWEB}.
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION].	**Norm, amp and filter:** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA]. **(SAMPLING TECH)** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
Sebe et al. (Sebe et al., 2006)	(HEAD, EYEBROWS, EYELIDS, MOUTH, VOLUME, SPEECH, PITCH) [INTEGRATION].	**Conv. sign:** (HEAD, EYEBROWS, EYELIDS, MOUTH) [3D2D]. **(RED. DIM. AND RED. OBJS.)** (PITCH) [CORRELATION].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	(ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS].	**Norm, amp and filter:** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(BALANCING AND LABELING)** (STRESS) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
Partala et al. (Partala et al., 2005)	(EMG) and (EMOTIONS) [LABELING].	**Norm, amp and filter:** (EMG) [SIGAMP [HPF, LPF]]. **(NOISE, D. INC. AND INC.)** (EMG) [-EYEBLINK]. **(OTHER)** (EMG) [TTEST].
K. H. Kim et al. (K. H. Kim et al., 2004)	(ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT].	**Norm, amp and filter:** (EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(NOISE, D. INC. AND INC.)** (ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]]. **(SAMPLING TECH)** (ECG(HRV), EDA) [DECIMATION]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].

Haag et al. (Haag et al., 2004)	(ECG(HR)) [DY/DX, D^2Y/DX^2] and (PPF(BVP(HR)), RESP) [INTERVALSPLIT].	**<u>Norm, amp and filter:</u>** (ECG(HR)) [LPF [HPF]], (ECG(HR)) [[DY/DX, D2Y/DX2] [SIGSMOOTH]], (EDA) [NORM [LPF]], (EMG) [SIGSMOOTH] and <PPG(BVP(HR)), ECG, RESP, EDA, ST, EMG> [NORM]. **OTHER)** (PPG(BVP(HR))) [HISTOGRAM].
Nwe et al. (Nwe et al., 2001)	(SPEECH) [INTERVALSPLIT].	**<u>Conv. sign:</u>** (SPEECH) [FOURIER]. **<u>Norm, amp and filter:</u>** (SPEECH) [SIGSMOOTH].
Vrijkotte et al. (Vrijkotte et al., 2000)	(PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]].	**(NOISE, D. INC. AND INC.)** (BP(SBP, DBP)) [-NOISE, -OUTLIERS]. **(SAMPLING TECH)** (STRESS) [INTENTIONAL, STRATIFIED]. **(BALANCING AND LABELING)** BP(SBP, DBP) [LABELING]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
Ritz et al. (Ritz et al., 2000)	(BP(SBP)) [INTERVALSPLIT].	**(RED. DIM. AND RED. OBJS.)** (BP(SBP)) [CORRELATION]. **(OTHER)** (HR, BP(SBP, DBP), ROS, RR, VT, EDA, EMOTIONS) [ANOVA].
L. S. Chen et al. (L. S. Chen et al., 1998)	(SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX].	**<u>Conv. sign:</u>** (EYES, MOUTH) [FOURIER]. **<u>Norm, amp and filter:</u>** (PITCH) [NORM]. **(NOISE, D. INC. AND INC.)** (EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].
R Sinha et al. (R Sinha et al., 1992)	(ECG) [R-R].	**<u>Norm, amp and filter:</u>** (ECG(HR)) [SIGAMP]. **(NOISE, D. INC. AND INC.)** (ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA]. **(RED. DIM. AND RED. OBJS.)** (BP(SBP, DBP), ECG(HR)) [MANSELECT].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.2.4. Analysis

Classification algorithms may not be able to use data in its RAW format because of its sensitivity to certain types of data or the existence of different numerical ranges between attributes (Gama et al., 2012). The algorithms do not interpret the nature of values or units of measurement, seeing them only as possibly correlatable data (Gama et al., 2012).

The wide diversity of sensors used in the investigations (i.e. brands, features, purposes), means that the collected data may contain discrepancies that require pre-processing: i) incompatible formats may be collected with conversion needs (e.g. Singh et al. and Agrawal et al. resorted to video to image conversion (i.e. VIDEO-PICS) in their investigations (Singh et al., 2015) (Agrawal et al., 2013)) (Gama et al., 2012); there may be different units of measurement or contain different amplitudes making it necessary to standardize them (e.g. Mandryk & Atkins normalized three physiological signals (cf. ECG, EMG and EDA) to a percentage value (Mandryk & Atkins, 2007)) (Basu et al., 2016) (Gama et al., 2012); and iii) there may be a need to generate new signals that more clearly, explicitly, or probably mirror the information present in an original signal (e.g. Zhao et al. calculated the D^2Y/DX^2 of the RESP signal and HR (Zhao et al., 2016) and Jaques et al. integrated data about the LOCAL in order to generate data about the paths traveled by participants in their experiment (i.e. PATHSTAKEN) (Jaques et al., 2015)).

In the literature under review, there are many researchers working on VIDEO and PICTURES that use signal conversion. However, there are also many investigations that do signal conversion between domains (e.g. time to frequencies), using techniques such as FOURIER, ZTRANSFORM, HHT or FD. The use of signal conversion techniques is natural given the need for signal processing that the data is subjected to. Although few authors report the use of data type conversion, we believe that they are frequently used techniques, and are only not fully reported due to the implicit character that can be assumed in the data processing and transformation processes.

The use of normalization is wide and transversal to the different types of signals treated by the researches analyzed. The large use of techniques related to normalization, amplification and filters on the signal, reveals the concern of the authors to ensure the efficiency of the algorithms by improving the quality of their input (e.g. Zhai & Barreto amplified the ST collected on the fingertip, applied an LPF to remove possible noise and, in the end, normalized the resulting values (i.e. (ST) [SIGAMP [LPF [NORM]]]) (Zhai & Barreto, 2006)).

Segmentation and de novo signal generation are important techniques because of their ability to transform the original signal into richer, more pertinent information for the algorithms by deducing new signal from another. The additional use of signals derived from the original, can allow the algorithms to work with information at a higher level of abstraction than the original data. Of the research under review, the use of techniques related to separating the signal into bands and intervals (i.e. BANDS and INTERVALSPLIT), and the use of new signals such as DY/DX and D^2Y/DX^2. To emphasize the weak use of data related to people's daily activities, spaces usually frequented and paths traveled (i.e. ADL, USUALPLACES, PATHSTAKEN) which, we believe, can contribute to a more efficient emotional recognition.

We also believe that INTEGRATION-related techniques are used more frequently. Perhaps they are not always reported by the authors, due to the fact that they consider them to be implicit in the initial dataset preparation process itself.

RESEARCH	CONV. SIGNAL	NORM, AMP AND FILTER	SEC. E GER. SINAL	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)		(EMG) [BPF, SIGAMP, NORM].		**(RED. DIM. AND RED. OBJS.)** (EMG) [SCATTER, LDA [AGGREGATION]].
S. H. Lee et al. (S. H. Lee et al., 2016)		(EYEBROWS, EYELIDS) [NORM].		**(NOISE, D. INC. AND INC.)** (FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)) [FAKEDATA]. **(OTHER)**

				(FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH) [CLUSTERING, SPARSEREP] and (EYEBROWS, EYELIDS) [FINDREGION, CROP]. {HAC}.
Eckert et al. (Eckert et al., 2016)	(EYES, EYEBROWS, NOSE, MOUTH) [GREYSCALE [BINARY]].	(EYES, EYEBROWS, NOSE, MOUTH) [IMGCONTRAST].		**(OTHER)** (EYES, EYEBROWS, NOSE, MOUTH) [FINDREGION, [GREYSCALE [BINARY [MORPHOPS]]] and (FACS, CAU) [MOTIONDETECT].
Matlovic et al. (Matlovic et al., 2016)			(EEG) [DWT].	
Sano & Eng (Sano & Eng, 2016)		(EDA) [LPF [NORM]].	(EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING]. **(OTHER)** (ACC) [MOTIONDETECT].
Zhao et al. (Zhao et al., 2016)		(RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF].	(RESP, HR) [D2Y/DX2, ZHAO2].	**(NOISE, D. INC. AND INC.)** (RESP, HR) [-NOISE]. **(OTHER)** (RESP) [LPF [PEAKDETECT]].
Zenonos et al. (Zenonos et al., 2016)		(IBI) [NORM].	(IBI) [BANDS].	**(NOISE, D. INC. AND INC.)** (MOOD, EMOTIONS) [TOLERANCE]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING].
Basu et al. (Basu et al., 2016)		(ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM].		**(RED. DIM. AND RED. OBJS.)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM [MANSELECT]]. **(OTHER)** {KHRV, WEKA, LABCHART, MATLAB, ORIGIN}.
Aracena et al. (Aracena et al., 2016)		(PUPIL) [LPF, NORM].		**(NOISE, D. INC. AND INC.)** (PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE]. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].
Adams & Robinson (Adams & Robinson, 2015)		(FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)) [NORM].		**(OTHER)** (GAZE) [FINDREGION].
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	(SPPECH) [FOURIER].	(SPPECH) [SIGAMP].	(SPEECH) [[FOURIER, SIGAMP] [INTERVALSPLIT, DY/DX, D^2Y/DX^2]].	

Lalitha et al. (Lalitha et al., 2015)			(SPEECH) [DWT].	
Singh et al. (Singh et al., 2015)	(SHOULDERS, HANDS) [VIDEO-PICS].		(SHOULDERS, HANDS) [VIDEO-PICS [-IMGBKG]].	
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)		(ECG, EDA) [LPF].	(ECG, ICG) [SIGSPLIT].	**(NOISE, D. INC. AND INC.)** (ECG, ICG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI]. **(OTHER)** (ECG) [PEAKDETECT].
Jaques et al. (Jaques et al., 2015)		(EDA) [LPF [NORM]] and <ACC> [NORM].	(LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX].	**(NOISE, D. INC. AND INC.)** (EDA) [LPF [NORM [-**PEAK**]]], (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(RED. DIM. AND RED. OBJS.)** (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT]. **(BALANCING AND LABELING)** (HAPPY) [LABELING].
Cruz et al. (Cruz et al., 2015)		(EOG) [GMP].	(EOG) [INTERVALSPLIT].	
Saha et al. (Saha et al., 2014)	(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [VIDEO-PICS].		(HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [-IMGBKG].	
Matiko et al. (Matiko et al., 2014)		(EDA) [FDA [NORM]].		**(RED. DIM. AND RED. OBJS.)** (EEG) [SCATTER, FDA]. **(BALANCING AND LABELING)** (EDA) [LABELING].
Bogomolov et al. (Bogomolov et al., 2014)		(PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [NORM].		**(RED. DIM. AND RED. OBJS.)** (PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER) [CORELATION, BOGOMOLOV [MANSELECT]].
Agrawal et al. (Agrawal et al., 2013)	(EYES, MOUTH, LIPS, SKIN) [VIDEO-PICS].			**(OTHER)** (SKIN, EYES, MOUTH) [FINDREGION]. {MATLAB}.
Soleymani et al. (Soleymani et al., 2013)	(EEG) [FOURIER].	(HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM].	(EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX]	**(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(SAMPLING TECH)**

			and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION].	[HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING]. **(OTHER)** {FEELTRACE}.
Vermun et al. (Vermun et al., 2013)	(HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP and KNEES) [VIDEO-PICS].			
Kusserow et al. (Kusserow et al., 2013)			(ACC) [TASKSPLIT] and (HR, ACC) [INTEGRATION].	
Nawasalkar et al. (Nawasalkar et al., 2013)	(NIBP, RESP(RR)) [HHT].			
Sano & Picard (Sano & Picard, 2013b)		(EDA) [LPF].	(EDA) [LPF [DY/DX]] and (ACC) [ADL].	**(RED. DIM. AND RED. OBJS.)** <EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS]. **(OTHER)** (EDA) [[LPF [DY/DX [PEAKDETECT]]]].
Raudonis (Raudonis, 2013)	(PUPIL) [GREYSCALE].			**(OTHER)** (PUPIL) [FINDREGION, RAUDONIS2].
Kawai et al. (Kawai et al., 2013)	(PUPIL) [BINARY].	(PUPIL) <DIAMETER> [KAWAI2 [NORM]].		**(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION]. **(OTHER)** (PUPIL) [FINDREGION, CLUSTERING, KAWAI1].
Babiker et al. (Babiker et al., 2013)		<PUPIL> [NORM].	(PUPIL) <INTERVALSPLIT>.	**(NOISE, D. INC. AND INC.)** (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]] **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC]. **(OTHER)** (PUPIL) [FINDREGION].
LikamWa et al. (LiKamWa et al., 2013)		(CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS)	(MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]].	**(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)**

		[LABELING] <COUNT, DURATION> [NORM].		<MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING]. **(OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
Murad & Malkawi (Murad & Malkawi, 2012)			(EEG, HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS].	**(BALANCING AND LABELING)** (HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS [LABELING]].
C. Y. Chang et al. (Chang et al., 2012)		(ECG, PR, BVP, EDA) [LPF, HPF, NORM].	(ECG, PR, BVP, EDA) [R-R].	**(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Bauer & Lukowicz (Bauer & Lukowicz, 2012)			(LOCAL) [INTEGRATION, USUALPLACES].	
Yang & Bhanu (S. Yang & Bhanu, 2011)	(HEAD, FACE) [VIDEO-PICS].	(HEAD, FACE) [VIDEO-PICS [IMGALIGN]].		**(OTHER)** (HEAD, FACE) [FINDREGION, YANG1].
Dhall et al. (Dhall et al., 2011)	(FACE) [VIDEO-PICS].	(FACE) [VIDEO-PICS [NORM]].		**(RED. DIM. AND RED. OBJS.)** (FACE) [VIDEO-PICS [-FRAMES [PCA]]. **(OTHER)** (FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(PUPIL) [VIDEO-PICS].	(PUPIL) [IMGSIZE, IMGINTENSITY].	(ECG(HRV)) [BANDS].	**(NOISE, D. INC. AND INC.)** (PUPIL) [-NOISE, -EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HRV), PPG, PUPIL> [GA]. **(OTHER)**

				(PUPIL) [FINDREGION, BLINKDETECT].
Hernandez et al. (Hernandez et al., 2011)		(EDA, STRESS) [NORM] and <EDA, STRESS> [NORM].		**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(BALANCING AND LABELING)** (CALL) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
N. Lane et al. (N. Lane et al., 2011)			(ACC) [ADL].	**(NOISE, D. INC. AND INC.)** (SLEEP, PHYSI) [MANINSERT]. **(OTHER)** (SLEEP) [LANE1] and (SLEEP, PHYSI) [MANADJUST].
H. Wang et al. (H. Wang et al., 2010)		(EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]].	(EYES) [-IMGBKG].	**(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST]. **(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING]. **(OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].
Bos (Bos, 2010)	(EEG) [-NOISE [BPF [FOURIER]]].	(EEG) [-NOISE [BPF].	(EEG) [-NOISE [BPF [FOURIER [BANDS]]]].	**(NOISE, D. INC. AND INC.)** (EEG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <EEG> [PCA]. **(OTHER)** {EEGLAB}.
Y. Liu et al. (Y. Liu et al., 2010)	(EEG) [FD] and [EMOTIONS] [2D-DISCRETE].	<EEG> [GMP].	<EEG> [INTERVALSPLIT].	
Setz et al. (Setz et al., 2010)		(EDA) [SIGAMP, LPF [HPF [LPF]]]		**(NOISE, D. INC. AND INC.)** (EDA) [DISCARDDATA, MANADJUST [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** <EDA> [WFA]. **(OTHER)** (EDA) [PEAKDETECT].
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV)) [FOURIER].	(ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM].	(ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D^2Y/DX^2]].	**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Lichtenstein et al.		(EDA) [LPF].		**(NOISE, D. INC. AND INC.)** (RESP) [-PEAK]. **(RED. DIM. AND RED. OBJS.)**

(Lichtenstein, Antje; Oehme, 2008)				<ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT]. **(BALANCING AND LABELING)** (RESP(RR)) <AMP> [LABELING].
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)		(PUPIL, EDA) [NORM].		**(NOISE, D. INC. AND INC.)** (PUPIL) [FAKEDATA].
Gunes & Piccardi (Gunes & Piccardi, 2007)	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY].	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST].	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG].	**(RED. DIM. AND RED. OBJS.)** (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST]. **(OTHER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.
Castellano et al. (Castellano et al., 2007)		(ARMS) <MOTION <MAX, MIN>> [NORM].	(ARMS) [-IMGBKG].	**(RED. DIM. AND RED. OBJS.)** (ARMS) [DISCARDDATA]. **(OTHER)** {EYESWEB}.
Mandryk & Atkins (Mandryk & Atkins, 2007)		(ECG(HR)) [FAKEDATA [SIGSMOOTH[NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]].	(ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION].	**(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA]. **(SAMPLING TECH)** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
Sebe et al. (Sebe et al., 2006)	(HEAD, EYEBROWS, EYELIDS, MOUTH) [3D2D].		(HEAD, EYEBROWS, EYELIDS, MOUTH, VOLUME, SPEECH, PITCH) [INTEGRATION].	**(RED. DIM. AND RED. OBJS.)** (PITCH) [CORRELATION].
Zhai & Barreto (Zhai & Barreto, 2006)		(ST) [SIGAMP [LPF [NORM]]] and (BVP(IBI), EDA) [NORM].		**(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER>[-NOISE [FAKEDATA]].

J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)		(STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH].	(ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS].	**(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(BALANCING AND LABELING)** (STRESS) [LABELING]. **(OTHER)** (EDA) [PEAKDETECT].
Herbon et al. (Herbon et al., 2005)	(HR, EDA, ST, PUPIL) [ZTRANSFORM].			**(NOISE, D. INC. AND INC.)** (HR, EDA, PUPIL, EMOTIONS) [DISCARDDATA] and (HR, EDA, PUPIL) <STD <THRESHOLD>> [DISCARDDATA].
Partala et al. (Partala et al., 2005)		(EMG) [SIGAMP [HPF, LPF]].	(EMG) and (EMOTIONS) [LABELING].	**(NOISE, D. INC. AND INC.)** (EMG) [-EYEBLINK]. **(OTHER)** (EMG) [TTEST].
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		(HR, EDA, ST) [NORM].		
K. H. Kim et al. (K. H. Kim et al., 2004)		(EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH].	(ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT].	**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]]. **(SAMPLING TECH)** (ECG(HRV), EDA) [DECIMATION]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Haag et al. (Haag et al., 2004)		(ECG(HR)) [LPF [HPF]], (ECG(HR)) [[DY/DX, D2Y/DX2] [SIGSMOOTH]], (EDA) [NORM [LPF]], (EMG) [SIGSMOOTH] and <PPG(BVP(HR)), ECG, RESP, EDA, ST, EMG> [NORM].	(ECG(HR)) [DY/DX, D^2Y/DX^2] and (PPF(BVP(HR)), RESP) [INTERVALSPLIT].	**(OTHER)** (PPG(BVP(HR))) [HISTOGRAM].
Nwe et al. (Nwe et al., 2001)	(SPEECH) [FOURIER].	(SPEECH) [SIGSMOOTH].	(SPEECH) [INTERVALSPLIT].	
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	(RESP) [FOURIER].	(PPG(BVP(HR)), ECG(HR, HRV), RESP, EDA) [SIGSMOOTH, NORM].		**(BALANCING AND LABELING)** (EMG) [LABELING]. **(OTHER)** {MATLAB}.
Vrijkotte et al.			(PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))),	**(NOISE, D. INC. AND INC.)**

(Vrijkotte et al., 2000)			ACC) [INTEGRATION [ADL]].	(BP(SBP, DBP)) [-NOISE, -OUTLIERS]. **(SAMPLING TECH)** (STRESS) [INTENTIONAL, STRATIFIED]. **(BALANCING AND LABELING)** BP(SBP, DBP) [LABELING]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
Ritz et al. (Ritz et al., 2000)			(BP(SBP)) [INTERVALSPLIT].	**(RED. DIM. AND RED. OBJS.)** (BP(SBP)) [CORRELATION]. **(OTHER)** (HR, BP(SBP, DBP), ROS, RR, VT, EDA, EMOTIONS) [ANOVA].
L. S. Chen et al. (L. S. Chen et al., 1998)	(EYES, MOUTH) [FOURIER].	(PITCH) [NORM].	(SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX].	**(NOISE, D. INC. AND INC.)** (EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].
J. Healey & Picard (J. Healey & Picard, 1998)		(RESP) [NORM], <RESP> [NORM] and (EDA) [SIGSMOOTH, NORM].		**(BALANCING AND LABELING)** (EMG, EDA, PPG(BVP(HR)), RESP) [LABELING].
Rajita Sinha (Rajita Sinha, 1996)		(EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM].		**(NOISE, D. INC. AND INC.)** (BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EMG) [MANSELECT]. **(SAMPLING TECH)** (EMG, ST) [SYSTEMATIC].
Scott R. Vrana (Scott R. Vrana, 1993)	(EMOTIONS) [QUALI-QUANTI].	(EMG) [SIGAMP, LPF, HPF].		**(NOISE, D. INC. AND INC.)** (ECG(HR)) [DISCARDDATA].
R Sinha et al. (R Sinha et al., 1992)		(ECG(HR)) [SIGAMP].	(ECG) [R-R].	**(NOISE, D. INC. AND INC.)** (ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA]. **(RED. DIM. AND RED. OBJS.)** (BP(SBP, DBP), ECG(HR)) [MANSELECT].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.3. SAMPLING AND META-INFORMATION

This section discusses sampling techniques that allow for the creation of data subsets (i.e. subsets of objects and attributes) in order to improve the performance of algorithms. Balancing between classes and enriching objects with meta-information (i.e. labeling) are also addressed.

Although the datasets may contain large volumes of information, it does not mean that all objects and attributes are necessary for the processing of the algorithms. Furthermore, the use of large datasets can lead to memory saturation or performance degradation in some algorithms (e.g. k-nearest neighbors (KNN)) (Gama et al., 2012) (Phinyomark et al., 2012). For this reason, researchers use samples in representation of the full dataset. The sample, in addition to being representative of the entire dataset, must also meet inter-class balancing. When an unbalanced dataset is used, algorithms tend to classify in the majority class (i.e. class with the largest number of objects) (Gama et al., 2012).

4.3.1. Sampling Techniques

Balancing the amount of data and computational performance is a challenge for induction processes (Gama et al., 2012). If on the one hand, a larger dataset is associated with a higher hit rate of the classifiers, more data means more information to process, more computational burden and lower performance of the systems (Gama et al., 2012) (Zhao et al., 2016). This section presents the sampling techniques used by the authors of the literature under review in the pre-processing phase, i.e. after the context data collection process.

A sample is a subset of data of size n, representative of the main data set (i.e. the original population, universe or dataset) of size N (Pocinho, 2009) (Brandão, n.d.). The use of subsets of data instead of the full dataset reduces the amount of information to process and can promote increased performance of systems (Zhao et al., 2016). However, the sample must be representative of the original dataset, otherwise the quality of the results will be sacrificed to achieve performance (e.g. the mean of the attributes must be equivalent and the number of objects per class must be proportional) (Gama et al., 2012). Ideally, the sample should be small but representative of the original dataset from the point of view of its statistical distribution, to be able to draw information from the full dataset from a subset of it (Investopedia, 2017) (Gama et al., 2012). In signal processing, the reduction of the sampling rate (i.e. downsampling) is known as decimation **[DECIMATION**] (Lyons, 2004) (e.g. Kim et al. (K. H. Kim et al., 2004)).

There are several probabilistic techniques used for sampling: simple random sampling **[RANDOM]** in which the objects to be considered for the sample are drawn (e.g. Zhang et al. randomly chose objects from their experiment (Z. Zhang et al., 2016)); stratified sampling **[STRATIFIED]** in which objects are initially divided into subsets (i.e. strata) and then objects are selected within each subset (it is said proportional stratified when the amount of objects selected for the sample meets the amount of objects in each stratum); and systematic sampling **[SYSTEMATIC]** in which an object is selected at each interval r object occurrences ($r = N/n$), starting from the k drawn element ($0 < k \leq r$). Besides probabilistic techniques, other non-probabilistic (i.e. non-random) techniques are also used (e.g. intentional **[INTENTIONAL] sampling,** in which objects are selected based on a criterion defined by the researcher (IPLeiria, 2009)).

RESEARCH	SAMPLING AND META-INFORMATION	
	TEC. SAMPLING	OTHER
Z. Zhang et al. (Z. Zhang et al., 2016)	(HEAD, FACS) [RANDOM].	<u>**Balancing and labeling:**</u> (FACS) [LABELING]. **(RED. DIM. AND RED. OBJS.)** (HEAD, FACS) [PCA].

		(OTHER) (FACS) [FINDREGION, SI-SSM]. {ZFACE}.
Aracena et al. (Aracena et al., 2016)	(PUPIL) [SYSTEMATIC].	**(NOISE, D. INC. AND INC.)** (PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE]. **(NORM, AMP, AND FILTER)** (PUPIL) [LPF, NORM].
Soleymani et al. (Soleymani et al., 2013)	[HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC].	**<u>Balancing and labeling:</u>** (EMOTIONS) [LABELING]. **(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(OTHER)** {FEELTRACE}.
Babiker et al. (Babiker et al., 2013)	(PUPIL) [SYSTEMATIC].	**(NOISE, D. INC. AND INC.)** (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]]]. **(NORM, AMP, AND FILTER)** <PUPIL> [NORM]. **(SEC. AND GER. SIGNAL)** (PUPIL) <INTERVALSPLIT>. **(OTHER)** (PUPIL) [FINDREGION].
C. Y. Chang et al. (Chang et al., 2012)	(EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]].	**(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT]. **(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED].	**<u>Balancing and labeling:</u>** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING]. **(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA]. **(NORM, AMP, AND FILTER)** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
K. H. Kim et al. (K. H. Kim et al., 2004)	(ECG(HRV), EDA) [DECIMATION].	**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]]. **(NORM, AMP, AND FILTER)**

		(EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Vrijkotte et al. (Vrijkotte et al., 2000)	(STRESS) [INTENTIONAL, STRATIFIED].	**Balancing and labeling:** BP(SBP, DBP) [LABELING]. **(NOISE, D. INC. AND INC.)** (BP(SBP, DBP)) [-NOISE, -OUTLIERS]. **(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
Rajita Sinha (Rajita Sinha, 1996)	(EMG, ST) [SYSTEMATIC].	**(NOISE, D. INC. AND INC.)** (BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EMG) [MANSELECT]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.3.2. Balancing and labeling

Class balancing is a problem related to classification algorithms (Gama et al., 2012). When trained with an unbalanced dataset, algorithms tend to classify the new data always in the majority class (i.e. class with the largest number of objects) (Gama et al., 2012). The natural solution to this problem may involve collecting more context data. However, when it is not possible to increase the number of objects naturally, it becomes necessary to use artificial techniques to solve the balancing problem (e.g. resetting the dataset size by eliminating objects from crowded classes or inserting objects using statistical values such as median and mode of the attributes, etc.) (Gama et al., 2012). The researchers considered in this literature survey mainly used artificial data generation **[+ARTIFICIALDATA]** to correct the distribution of the number of objects per class (i.e. increasing synthetic objects to minority classes) (e.g. Wang et al. considered duplicate images collected with eyes closed to improve the balance with images with eyes open (H. Wang et al., 2010), Gogia et al. resorted to +ARTIFICIALDATA to balance the number of objects in minority classes (Gogia et al., 2016), etc.). Some authors chose other ways to solve the balancing problem. Alzoubi et al. solved the problem of unbalancing between classes of data collected by self-reports by applying a WEKA downsampling technique **[SPREADSUBSAMPLE]** that produces a balanced random subset from the initial dataset (Algorithmia, 2017) ("Class SpreadSubsample," n.d.) (Alzoubi et al., 2013);

Labeling techniques **[LABELING]** are used by authors to annotate the data with additional supporting information. There are several authors who use LABELING to add meta-information to their data: Gogia et al. annotated the collected EEG signal with information about the attention state of their experiment participants while watching videos (i.e. used the value Patt to stand for "Paying attention" and P'att for "Not paying attention") (Gogia et al., 2016); Zhang et al. added metadata in their database about occurrence and intensity of changes in Action Units on their participants' faces (Z. Zhang et al., 2016); Zenonos et al. divided the MOOD intensities felt by the participants into classes in order to use them for classification (Zenonos et al., 2016); and Basu et al. labeled the images used in emotional induction according to their emotional intensity (e.g. high valence high arousal (HVHA), high valence low arousal (HVLA), etc.) (Basu et al., 2016).

RESEARCH	SAMPLING AND META-INFORMATION	
	BALANC. AND ETIQ.	OTHER
Gogia et al. (Gogia et al., 2016)	(EEG) [[[-EYEBLINK, -DUPLICATE] [LABELING]] [+ARTIFICIALDATA]].	**(NOISE, D. INC. AND INC.)** (EEG) [-EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** (EEG) [-DUPLICATE].
Z. Zhang et al. (Z. Zhang et al., 2016)	(FACS) [LABELING].	**<u>Sampling tech:</u>** (HEAD, FACS) [RANDOM]. **(RED. DIM. AND RED. OBJS.)** (HEAD, FACS) [PCA]. **(OTHER)** (FACS) [FINDREGION, SI-SSM]. {ZFACE}.
Sano & Eng (Sano & Eng, 2016)	(SLEEP, EDA) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(OTHER)** (ACC) [MOTIONDETECT].
Zenonos et al. (Zenonos et al., 2016)	(EMOTIONS) [LABELING].	**(NOISE, D. INC. AND INC.)** (MOOD, EMOTIONS) [TOLERANCE]. **(NORM, AMP, AND FILTER)** (IBI) [NORM]. **(SEC. AND GER. SIGNAL)** (IBI) [BANDS].
Turan et al. (Turan et al., 2015)	(FACE, EYES) [LABELING].	**(RED. DIM. AND RED. OBJS.)** (FACE, EYES) [SLPP, DCC]. **(OTHER)** (EYES) [FINDREGION].
Jaques et al. (Jaques et al., 2015)	(HAPPY) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA) [LPF [NORM [**-PEAK]]]**, (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(RED. DIM. AND RED. OBJS.)** (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]] and <ACC> [NORM]. **(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX].
Matiko et al.	(EDA) [LABELING].	**(RED. DIM. AND RED. OBJS.)**

(Matiko et al., 2014)		(EEG) [SCATTER, FDA]. **(NORM, AMP, AND FILTER)** (EDA) [FDA [NORM]].
Soleymani et al. (Soleymani et al., 2013)	(EMOTIONS) [LABELING].	<u>**Sampling tech:**</u> [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(OTHER)** {FEELTRACE}.
Alzoubi et al. (Alzoubi et al., 2013)	(ECG(HRV), RESP, EDA, EMG) [SPREADSUBSAMPLE].	**(RED. DIM. AND RED. OBJS.)** (ECG(HRV), RESP, EDA, EMG) [X^2]. **(OTHER)** {AUBT}.
LikamWa et al. (LiKamWa et al., 2013)	(MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING].	**(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(SEC. AND GER. SIGNAL)** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
Murad & Malkawi (Murad & Malkawi, 2012)	(HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS [LABELING]].	**(SEC. AND GER. SIGNAL)** (EEG, HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS].
Hernandez et al. (Hernandez et al., 2011)	(CALL) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(NORM, AMP, AND FILTER)** (EDA, STRESS) [NORM] and <EDA, STRESS> [NORM]. **(OTHER)** (EDA) [PEAKDETECT].
H. Wang et al. (H. Wang et al., 2010)	(EYES) [+ARTIFICIALDATA, LABELING].	**(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST]. **(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG].

		(OTHER) (EYES) [FINDREGION, CROP, COLORCORR].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	(RESP(RR)) <AMP> [LABELING].	**(NOISE, D. INC. AND INC.)** (RESP) [-PEAK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT]. **(NORM, AMP, AND FILTER)** (EDA) [LPF].
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR), EDA, EMG, EMOTIONS) [LABELING].	**<u>Sampling tech:</u>** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA]. **(NORM, AMP, AND FILTER)** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	(STRESS) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(OTHER)** (EDA) [PEAKDETECT].
Van Eck et al. (van Eck et al., 2005)	(STRESS) [LABELING].	**(NOISE, D. INC. AND INC.)** (HEALTH) [DISCARDDATA] and (CORT) [-OUTLIERS]. **(RED. DIM. AND RED. OBJS.)** (LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH) [PCA [AGGREGATION]].
Partala & Surakka (Partala & Surakka, 2003)	(PUPIL) [LABELING].	**(NOISE, D. INC. AND INC.)** (PUPIL) [DISCARDDATA, -EYEBLINK]. **(OTHER)** (PUPIL) [PEAKDETECT, TTEST].
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	(EMOTIONS) [LABELING].	
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	(EMG) [LABELING].	**(CONV. SINAL)** (RESP) [FOURIER]. **(NORM, AMP, AND FILTER)** (PPG(BVP(HR)), ECG(HR, HRV), RESP, EDA) [SIGSMOOTH, NORM].

		(OTHER) {MATLAB}.
Vrijkotte et al. (Vrijkotte et al., 2000)	BP(SBP, DBP) [LABELING].	**Sampling tech:** (STRESS) [INTENTIONAL, STRATIFIED]. **(NOISE, D. INC. AND INC.)** (BP(SBP, DBP)) [-NOISE, -OUTLIERS]. **(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
J. Healey & Picard (J. Healey & Picard, 1998)	(EMG, EDA, PPG(BVP(HR)), RESP) [LABELING].	**(NORM, AMP, AND FILTER)** (RESP) [NORM], <RESP> [NORM] and (EDA) [SIGSMOOTH, NORM].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.3.3. Analysis

The performance of the algorithms is related to the number of objects in the dataset and their processing may be penalized by large volumes of information (Zhao et al., 2016) (Gama et al., 2012). It is in this context that sampling techniques and criteria for sample definition (e.g. representativeness of the original data), assume an important role in the pre-processing phase (Zhao et al., 2016) (Investopedia, 2017). However, the definition of data subsets for use as input in classification algorithms, must also attend to balancing the number of objects between classes. Using unbalanced sets can lead to problems, as some algorithms tend to classify new data into the majority class (Gama et al., 2012).

Using samples as a representation of the full dataset is a common practice in research. Of the investigations under review, not many mention the sampling techniques used. However, most of the researchers who reported using such techniques chose to consider one object at each interval of object occurrences (i.e. SYSTEMATIC). Since usually the datasets collected in the context of emotional detection represent data in time (i.e. time-series), the choice for SYSTEMATIC will be related to the need to ensure in the sample objects from different moments of context data collection. This is also the justification for the low use of techniques such as RANDOM and INTENTIONAL, since their use would not ensure the temporal representativeness of the original sample dataset.

Although there are few investigations that show the use of balancing techniques, we believe that their use will be more expressive than what is reported. Still, of the investigations reviewed, we highlighted the use of +ARTIFICIALDATA as a way to fill gaps in balancing the number of objects from different classes, and the residual use of downsampling techniques in producing random but balanced subsets of the original dataset (Algorithmia, 2017) ("Class SpreadSubsample," n.d.) (Alzoubi et al., 2013).

Also noteworthy is the large number of authors who use LABELING techniques. The annotation of the original dataset with metadata allows adding useful information to the dataset. This metadata, often used as ground-truth, is important in the learning phase of algorithms. Emotion LABELING plays an important role in the context of research related to emotion detection, because it is the way generally used by researchers to add emotional ground-truth information to the datasets processed by the algorithms (i.e. intangible and directly measurable information (Kreibig, 2010)). LABELING of emotional information is used across data from the various collection contexts (cf. facial, oral expression, and body posture; physiological context; and social context).

RESEARCH	TEC. SAMPLING	BALANC. AND ETIQ.	OTHER
Gogia et al. (Gogia et al., 2016)		(EEG) [[[-EYEBLINK, -DUPLICATE] [LABELING]] [+ARTIFICIALDATA]].	**(NOISE, D. INC. AND INC.)** (EEG) [-EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** (EEG) [-DUPLICATE].
Z. Zhang et al. (Z. Zhang et al., 2016)	(HEAD, FACS) [RANDOM].	(FACS) [LABELING].	**(RED. DIM. AND RED. OBJS.)** (HEAD, FACS) [PCA]. **(OTHER)** (FACS) [FINDREGION, SI-SSM]. {ZFACE}.
Sano & Eng (Sano & Eng, 2016)		(SLEEP, EDA) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(OTHER)** (ACC) [MOTIONDETECT].
Zenonos et al. (Zenonos et al., 2016)		(EMOTIONS) [LABELING].	**(NOISE, D. INC. AND INC.)** (MOOD, EMOTIONS) [TOLERANCE]. **(NORM, AMP, AND FILTER)** (IBI) [NORM]. **(SEC. AND GER. SIGNAL)** (IBI) [BANDS].
Aracena et al. (Aracena et al., 2016)	(PUPIL) [SYSTEMATIC].		**(NOISE, D. INC. AND INC.)** (PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE]. **(NORM, AMP, AND FILTER)** (PUPIL) [LPF, NORM].
Turan et al. (Turan et al., 2015)		(FACE, EYES) [LABELING].	**(RED. DIM. AND RED. OBJS.)** (FACE, EYES) [SLPP, DCC]. **(OTHER)** (EYES) [FINDREGION].
Jaques et al. (Jaques et al., 2015)		(HAPPY) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA) [LPF [NORM [**-PEAK**]]], (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(RED. DIM. AND RED. OBJS.)** (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI,

			ALCOH DRUGS) [WFS, MANSELECT]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]] and <ACC> [NORM]. **(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX].
Matiko et al. (Matiko et al., 2014)		(EDA) [LABELING].	**(RED. DIM. AND RED. OBJS.)** (EEG) [SCATTER, FDA]. **(NORM, AMP, AND FILTER)** (EDA) [FDA [NORM]].
Soleymani et al. (Soleymani et al., 2013)	[HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC].	(EMOTIONS) [LABELING].	**(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(OTHER)** {FEELTRACE}.
Alzoubi et al. (Alzoubi et al., 2013)		(ECG(HRV), RESP, EDA, EMG) [SPREADSUBSAMPLE].	**(RED. DIM. AND RED. OBJS.)** (ECG(HRV), RESP, EDA, EMG) [X^2]. **(OTHER)** {AUBT}.
Babiker et al. (Babiker et al., 2013)	(PUPIL) [SYSTEMATIC].		**(NOISE, D. INC. AND INC.)** (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]]]. **(NORM, AMP, AND FILTER)** <PUPIL> [NORM]. **(SEC. AND GER. SIGNAL)** (PUPIL) <INTERVALSPLIT>. **(OTHER)** (PUPIL) [FINDREGION].
LikamWa et al. (LiKamWa et al., 2013)		(MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING].	**(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM].

			(SEC. AND GER. SIGNAL) (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(OTHER)** (CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
Murad & Malkawi (Murad & Malkawi, 2012)		(HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS [LABELING]].	**(SEC. AND GER. SIGNAL)** (EEG, HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS].
C. Y. Chang et al. (Chang et al., 2012)	(EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]].		**(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT]. **(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R]. **(OTHER)** (ECG, BVP, PR) [PEAKDETECT].
Hernandez et al. (Hernandez et al., 2011)		(CALL) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(NORM, AMP, AND FILTER)** (EDA, STRESS) [NORM] and <EDA, STRESS> [NORM]. **(OTHER)** (EDA) [PEAKDETECT].
H. Wang et al. (H. Wang et al., 2010)		(EYES) [+ARTIFICIALDATA, LABELING].	**(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST]. **(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG]. **(OTHER)** (EYES) [FINDREGION, CROP, COLORCORR].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)		(RESP(RR)) <AMP> [LABELING].	**(NOISE, D. INC. AND INC.)** (RESP) [-PEAK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT]. **(NORM, AMP, AND FILTER)** (EDA) [LPF].
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED].	(ECG(HR), EDA, EMG, EMOTIONS) [LABELING].	**(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA].

			(NORM, AMP, AND FILTER) (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(OTHER)** (ECG(HR), EDA, EMG) [HISTOGRAM].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)		(STRESS) [LABELING].	**(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(OTHER)** (EDA) [PEAKDETECT].
Van Eck et al. (van Eck et al., 2005)		(STRESS) [LABELING].	**(NOISE, D. INC. AND INC.)** (HEALTH) [DISCARDDATA] and (CORT) [-OUTLIERS]. **(RED. DIM. AND RED. OBJS.)** (LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH) [PCA [AGGREGATION]].
K. H. Kim et al. (K. H. Kim et al., 2004)	(ECG(HRV), EDA) [DECIMATION].		**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]]. **(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT]. **(OTHER)** (ECG(HR, HRV)) [PEAKDETECT].
Partala & Surakka (Partala & Surakka, 2003)		(PUPIL) [LABELING].	**(NOISE, D. INC. AND INC.)** (PUPIL) [DISCARDDATA, -EYEBLINK]. **(OTHER)** (PUPIL) [PEAKDETECT, TTEST].

Buchanan & Lovallo (Buchanan & Lovallo, 2001)		(EMOTIONS) [LABELING].	
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)		(EMG) [LABELING].	**(CONV. SINAL)** (RESP) [FOURIER]. **(NORM, AMP, AND FILTER)** (PPG(BVP(HR)), ECG(HR, HRV), RESP, EDA) [SIGSMOOTH, NORM]. **(OTHER)** {MATLAB}.
Vrijkotte et al. (Vrijkotte et al., 2000)	(STRESS) [INTENTIONAL, STRATIFIED].	BP(SBP, DBP) [LABELING].	**(NOISE, D. INC. AND INC.)** (BP(SBP, DBP)) [-NOISE, -OUTLIERS]. **(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]]. **(OTHER)** [AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
J. Healey & Picard (J. Healey & Picard, 1998)		(EMG, EDA, PPG(BVP(HR)), RESP) [LABELING].	**(NORM, AMP, AND FILTER)** (RESP) [NORM], <RESP> [NORM] and (EDA) [SIGSMOOTH, NORM].
Rajita Sinha (Rajita Sinha, 1996)		(EMG, ST) [SYSTEMATIC].	**(NOISE, D. INC. AND INC.)** (BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EMG) [MANSELECT]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.4. OTHER TECHNIQUES AND INSTRUMENTS

This section covers the techniques that support the application of other pre-processing techniques. As they were not considered in the previous sections, they are presented here. Also included in this section are the techniques used in data representation and the tools used in the pre-processing phase.

At the VIDEO, AUDIO and PICTURES processing level, the following pre-processing support techniques were identified: detection of regions or edges in images **[FINDREGION]** (e.g. Mokhayeri et al. used Genetic Algorithm (GA), Fuzzy Image Processing (FIP) to detect the eye and its edge (Mokhayeri & Toosizadeh, 2011); Eckert et al. used the Viola-Jones algorithm (Viola & Jones, 2004) algorithm to detect face and eyes (Eckert et al., 2016); Zhang et al. used the Constrained Local Model (CLM) to detect landmarks of the face (Cristinacce & Cootes, 2008) (Z. Zhang et al., 2016); etc.); blink detection **[BLINKDETECT]** in VIDEO (Mokhayeri & Toosizadeh, 2011); clustering **[CLUSTERING]** to identify image zones (e.g. Lee et al. used face recognition and cluster analysis in video sequences (S. H. Lee et al., 2016); Dhall et al. used the k-means algorithm (Duda et al., 2001) to perform CLUSTERING on images (Dhall et al., 2011)); crop **[CROP]** to crop images (e.g. Lee et al. used CROP to crop image faces (S. H. Lee et al., 2016); morphological operations **[MORPHOPS]** (e.g. Eckert et al. used MORPHOPS in BINARY images to recognize EYES, EYEBROWS, and MOUTH (Eckert et al., 2016)); Zhang et al. used the Index-based Statistical shape model **[SI-SSM]** to track properties directly from 3D faces (Z. Zhang et al., 2016); motion detection **[MOTIONDETECT)** (e.g. Eckert et al. detected motion in the face by analyzing changes between images (Eckert et al., 2016); and Sano & Eng. used MOTIONDETECT from ACC to determine ADLs (Sano & Eng, 2016.)); Raudonis created an algorithm for GAZE tracking that considered the influence of luminosity variation on PUPIL **[RAUDONIS2]** (Raudonis, 2013); and Kawai et al. used a proprietary technique to attenuate the effects of the specific brightness of each image presented to the participants in their experiment **[KAWAI1**] (Kawai et al., 2013).

<u>Other</u> context-specific collection techniques were also identified: Zhao et al. used peak detection in the RESP signal **[PEAKDETECT]** to identify each breath cycle (Zhao et al., 2016); and Lane et al. created an algorithm to estimate sleep duration based on the frequency and moments of smartphone battery recharging (e.g. absence of motion, silence of the surrounding environment, etc.) **[LANE1**] (N. Lane et al., 2011).

Some authors have also used <u>data representation</u> techniques to facilitate classification processes: Lee et al. used Sparse Representation **[SPARSEREP]** as a support for emotion classification based on face images (S. H. Lee et al., 2016) (SPARSEREP allows to represent the data in a more compact way (Wen, Jia, Lian, Zhou, & Lu, 2016), and combines machine learning techniques with compressed sensing (L. Zhang et al., 2012)) (Rigamonti, Brown, & Lepetit, 2011) (Wright, Yang, Ganesh, Sastry, & Ma, 2009); LikamWa et al. used histograms **[HISTOGRAM]** to evaluate the distribution of CALL, SMS, and EMAIL data (LiKamWa et al., 2013); Yang et al. created an algorithm for generalized representation of human faces in avatars **[YANG1**] (S. Yang & Bhanu, 2011); Wang et al. used Color Correlogram **[COLORCORR]** to represent each eye instead of contour and circle information (J. Huang, Kumar, Mitra, Zhu, & Zabih, 1997a) (J. Huang, Kumar, Mitra, Zhu, & Zabih, 1997b) (H. Wang et al., 2010); Partala et al. used t-tests **[TTEST]** to analyze the differences in valence levels felt by participants (T. K. Kim, 2015) (Ugoni & Walker, 1995) (Partala et al., 2005); and the VAR analysis **[ANOVA]** that allows finding differences between groups or experiments (Sthle & Wold, 1989) (Howard, 2012) (Martin, 1000).

Tools were also used in pre-processing: Lee et al. used MATLAB and the function Hierarchical Agglomerative Clustering to extract the transition of partial facial expressions (S. H. Lee et al., 2016) **[HAC**]; Zhang et al. used zface **[ZFACE**] to track facial expressions in 2D (Z. Zhang et al., 2016); Alzoubi et al. also used MATLAB-based Augsburg Biosignal Toolbox **[AUBT**] in the pre-processing and property extraction phase from raw data (Wagner, 2006) (Alzoubi et al., 2013); the KUBIOS HRV **[KHRV**] is a software for HRV analysis from Kubios (a company developing medical technology for physiological signal analysis (Tarvainen, Niskanen, Lipponen, Ranta-aho, & Karjalainen, 2014)), suitable for health-related research and used in various human and animal welfare investigations (Ditor et al., 2005) (e.g. Basu et al. analyzed the HRV of log data collected (Basu et al., 2016)); the Feeltrace **[FEELTRACE**] allows to track and elicit emotions simultaneously (Cowie et al., 2000) (e.g. Soleymani et al. used FEELTRACE to continuously annotate valence in the videos recorded in their experiment (Soleymani et al., 2013)); EEGLab **[EEGLAB**] is a tool that allows working on the EEG signal (e.g. Bos used the EEGLab GMP in segmenting the signal into BANDS (Bos, 2010)); the General Linear Models **[GLM**] is a SPSS tool used to analyze the relationship between variables (IBM Statistics, n.d.) and EyesWeb **[EYESWEB**] by Camurri et al., is an open-architecture, free-to-use software tool used for real-time monitoring of body motion based on video cameras and other sensors, occupancy analysis in 2D spaces for low-level motion extraction (e.g. gesture analysis), and trajectory analysis in 2D spaces (Camurri, Mazzarino, & Volpe, 2004)) (e.g., Castellano et al. used EYESWEB to extract data about silhouette and hands, and other movement-related variables (e.g. ACC) (Castellano et al., 2007)).

In addition to these tools, utilities or libraries not identified in detail but belonging to data analysis and processing platforms were used: the MATLAB **[MATLAB]** (The Mathworks Inc., 2016); the Origin [**ORIGIN**] is a graphical software for data analysis widely used in both research and professional activities (OriginLab Corporation, n.d.) (e.g. Basu et al. used ORIGIN (Basu et al., 2016)); the Waikato Environment for Knowledge Analysis [**WEKA**] is a tool that can be used directly or through its API, is composed of a set of machine learning (ML) algorithms used in data mining tasks, and contains tools for data pre-processing, classification, regression, clustering, association, and visualization (Machine Learning Group at the University of Waikato, n.d.) (there are several researchers using the WEKA tools: Basu et al. (Basu et al., 2016); Kumar et al. (Kumar & Chadha, 2011); Mower et al. (Mower, Matari, & Narayanan, 2011); Miluzzo et al. (Miluzzo et al., 2008); Papamatthaiakis et al. (Papamatthaiakis, Polyzos, & Xylomenos, 2010); Chen et al (Z. Chen et al., 2013); Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008); Alzoubi et al used WEKA for data classification (Alzoubi et al., 2013); etc.).

RESEARCH	PRE-PROCESSING	
	OTHERS	PREVIOUS
S. H. Lee et al. (S. H. Lee et al., 2016)	(FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH) [CLUSTERING, SPARSEREP] and (EYEBROWS, EYELIDS) [FINDREGION, CROP]. {HAC}.	**(NOISE, D. INC. AND INC.)** (FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)) [FAKEDATA]. **(NORM, AMP, AND FILTER)** (EYEBROWS, EYELIDS) [NORM].
Eckert et al. (Eckert et al., 2016)	(EYES, EYEBROWS, NOSE, MOUTH) [FINDREGION, [GREYSCALE [BINARY [MORPHOPS]]] and (FACS, CAU) [MOTIONDETECT].	**(CONV. SINAL)** (EYES, EYEBROWS, NOSE, MOUTH) [GREYSCALE [BINARY]]. **(NORM, AMP, AND FILTER)** (EYES, EYEBROWS, NOSE, MOUTH) [IMGCONTRAST].
Z. Zhang et al. (Z. Zhang et al., 2016)	(FACS) [FINDREGION, SI-SSM]. {ZFACE}.	**(RED. DIM. AND RED. OBJS.)** (HEAD, FACS) [PCA]. **(SAMPLING TECH)** (HEAD, FACS) [RANDOM]. **(BALANCING AND LABELING)** (FACS) [LABELING].
Sano & Eng (Sano & Eng, 2016)	(ACC) [MOTIONDETECT].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]]. **(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC) [MOTIONDETECT [ADL]]. **(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING].
Zhao et al. (Zhao et al., 2016)	(RESP) [LPF [PEAKDETECT]].	**(NOISE, D. INC. AND INC.)** (RESP, HR) [-NOISE]. **(NORM, AMP, AND FILTER)** (RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF]. **(SEC. AND GER. SIGNAL)** (RESP, HR) [D2Y/DX2, ZHAO2].

Basu et al. (Basu et al., 2016)	{KHRV, WEKA, LABCHART, MATLAB, ORIGIN}.	**(RED. DIM. AND RED. OBJS.)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM [MANSELECT]]. **(NORM, AMP, AND FILTER)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM].
Adams & Robinson (Adams & Robinson, 2015)	(GAZE) [FINDREGION].	**(NORM, AMP, AND FILTER)** (FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)) [NORM].
Turan et al. (Turan et al., 2015)	(EYES) [FINDREGION].	**(RED. DIM. AND RED. OBJS.)** (FACE, EYES) [SLPP, DCC]. **(BALANCING AND LABELING)** (FACE, EYES) [LABELING].
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)	(ECG) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (ECG, ICG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI]. **(NORM, AMP, AND FILTER)** (ECG, EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (ECG, ICG) [SIGSPLIT].
Agrawal et al. (Agrawal et al., 2013)	(SKIN, EYES, MOUTH) [FINDREGION]. {MATLAB}.	**(CONV. SINAL)** (EYES, MOUTH, LIPS, SKIN) [VIDEO-PICS].
Soleymani et al. (Soleymani et al., 2013)	{FEELTRACE}.	**(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE]. **(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION]. **(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING].
Alzoubi et al. (Alzoubi et al., 2013)	{AUBT}.	**(RED. DIM. AND RED. OBJS.)** (ECG(HRV), RESP, EDA, EMG) [X^2]. **(BALANCING AND LABELING)** (ECG(HRV), RESP, EDA, EMG) [SPREADSUBSAMPLE].
Sano & Picard (Sano & Picard, 2013b)	(EDA) [[LPF [DY/DX [PEAKDETECT]]]].	**(RED. DIM. AND RED. OBJS.)** <EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS]. **(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [DY/DX]] and (ACC) [ADL].
Raudonis (Raudonis, 2013)	(PUPIL) [FINDREGION, RAUDONIS2].	**(CONV. SINAL)** (PUPIL) [GREYSCALE].
Kawai et al. (Kawai et al., 2013)	(PUPIL) [FINDREGION, CLUSTERING, KAWAI1].	**(NOISE, D. INC. AND INC.)**

		(PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION]. **(CONV. SINAL)** (PUPIL) [BINARY]. **(NORM, AMP, AND FILTER)** (PUPIL) <DIAMETER> [KAWAI2 [NORM]].
Babiker et al. (Babiker et al., 2013)	(PUPIL) [FINDREGION].	**(NOISE, D. INC. AND INC.)** (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]]]. **(NORM, AMP, AND FILTER)** <PUPIL> [NORM]. **(SEC. AND GER. SIGNAL)** (PUPIL) <INTERVALSPLIT>. **(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].
LikamWa et al. (LiKamWa et al., 2013)	(CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].	**(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION]. **(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(SEC. AND GER. SIGNAL)** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]]. **(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING].
C. Y. Chang et al. (Chang et al., 2012)	(ECG, BVP, PR) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT]. **(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R]. **(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]].
Yang & Bhanu (S. Yang & Bhanu, 2011)	(HEAD, FACE) [FINDREGION, YANG1].	**(CONV. SINAL)** (HEAD, FACE) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (HEAD, FACE) [VIDEO-PICS [IMGALIGN]].
Dhall et al. (Dhall et al., 2011)	(FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].	**(RED. DIM. AND RED. OBJS.)** (FACE) [VIDEO-PICS [-FRAMES [PCA]]. **(CONV. SINAL)** (FACE) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (FACE) [VIDEO-PICS [NORM]].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	(PUPIL) [FINDREGION, BLINKDETECT].	**(NOISE, D. INC. AND INC.)** (PUPIL) [-NOISE, -EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HRV), PPG, PUPIL> [GA]. **(CONV. SINAL)** (PUPIL) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)**

		(PUPIL) [IMGSIZE, IMGINTENSITY]. **(SEC. AND GER. SIGNAL)** (ECG(HRV)) [BANDS].
Hernandez et al. (Hernandez et al., 2011)	(EDA) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(NORM, AMP, AND FILTER)** (EDA, STRESS) [NORM] and <EDA, STRESS> [NORM]. **(BALANCING AND LABELING)** (CALL) [LABELING].
N. Lane et al. (N. Lane et al., 2011)	(SLEEP) [LANE1] and (SLEEP, PHYSI) [MANADJUST].	**(NOISE, D. INC. AND INC.)** (SLEEP, PHYSI) [MANINSERT]. **(SEC. AND GER. SIGNAL)** (ACC) [ADL].
H. Wang et al. (H. Wang et al., 2010)	(EYES) [FINDREGION, CROP, COLORCORR].	**(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST]. **(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG]. **(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING].
Bos (Bos, 2010)	{EEGLAB}.	**(NOISE, D. INC. AND INC.)** (EEG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <EEG> [PCA]. **(CONV. SINAL)** (EEG) [-NOISE [BPF [FOURIER]]]. **(NORM, AMP, AND FILTER)** (EEG) [-NOISE [BPF]. **(SEC. AND GER. SIGNAL)** (EEG) [-NOISE [BPF [FOURIER [BANDS]]]].
Setz et al. (Setz et al., 2010)	(EDA) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (EDA) [DISCARDDATA, MANADJUST [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** <EDA> [WFA]. **(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, LPF [HPF [LPF]]]
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV)) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS]. **(CONV. SINAL)** (ECG(HR, HRV)) [FOURIER]. **(NORM, AMP, AND FILTER)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]].
Gunes & Piccardi (Gunes & Piccardi, 2007)	(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS,	**(RED. DIM. AND RED. OBJS.)** (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW,

	NECK) [MORPHOPS, FINDREGION]. {WEKA}.	SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST]. **CONV. SIGNAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY]. **(NORM, AMP, AND FILTER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [IMGSIZE, IMGCONTRAST]. **(SEC. AND GER. SIGNAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG].
Castellano et al. (Castellano et al., 2007)	{EYESWEB}.	**(RED. DIM. AND RED. OBJS.)** (ARMS) [DISCARDDATA]. **(NORM, AMP, AND FILTER)** (ARMS) <MOTION <MAX, MIN>> [NORM]. **(SEC. AND GER. SIGNAL)** (ARMS) [-IMGBKG].
Mandryk & Atkins (Mandryk & Atkins, 2007)	(ECG(HR), EDA, EMG) [HISTOGRAM].	**(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA]. **(NORM, AMP, AND FILTER)** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION]. **(SAMPLING TECH)** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING].
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	(EDA) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)** <EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT]. **(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS]. **(BALANCING AND LABELING)** (STRESS) [LABELING].
Partala et al. (Partala et al., 2005)	(EMG) [TTEST].	**(NOISE, D. INC. AND INC.)** (EMG) [-EYEBLINK]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP [HPF, LPF]]. **(SEC. AND GER. SIGNAL)** (EMG) and (EMOTIONS) [LABELING].

Busso et al. (Busso et al., 2004)	(FOREHEAD, EYEBROWS, EYES, CHEEKS) [FINDREGION, CLUSTERING].	**(RED. DIM. AND RED. OBJS.)** <PITCH, VOLUME> [SBS], <FOREHEAD, EYEBROWS, EYES, CHEEKS> [PCA] and <PITCH, VOLUME, FOREHEAD, EYEBROWS, EYES, CHEEKS> [SBS [AGGREGATION], MANSELECT].
K. H. Kim et al. (K. H. Kim et al., 2004)	(ECG(HR, HRV)) [PEAKDETECT].	**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]]. **(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, BPF] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT]. **(SAMPLING TECH)** (ECG(HRV), EDA) [DECIMATION].
Haag et al. (Haag et al., 2004)	(PPG(BVP(HR))) [HISTOGRAM].	**(NORM, AMP, AND FILTER)** (ECG(HR)) [LPF [HPF]], (ECG(HR)) [[DY/DX, D2Y/DX2] [SIGSMOOTH]], (EDA) [NORM [LPF]], (EMG) [SIGSMOOTH] and <PPG(BVP(HR)), ECG, RESP, EDA, ST, EMG> [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR)) [DY/DX, D2Y/DX2] and (PPF(BVP(HR)), RESP) [INTERVALSPLIT].
Partala & Surakka (Partala & Surakka, 2003)	(PUPIL) [PEAKDETECT, TTEST].	**(NOISE, D. INC. AND INC.)** (PUPIL) [DISCARDDATA, -EYEBLINK]. **(BALANCING AND LABELING)** (PUPIL) [LABELING].
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	{MATLAB}.	**(CONV. SINAL)** (RESP) [FOURIER]. **(NORM, AMP, AND FILTER)** (PPG(BVP(HR)), ECG(HR, HRV), RESP, EDA) [SIGSMOOTH, NORM]. **(BALANCING AND LABELING)** (EMG) [LABELING].
Vrijkotte et al. (Vrijkotte et al., 2000)	[AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.	**(NOISE, D. INC. AND INC.)** (BP(SBP, DBP)) [-NOISE, -OUTLIERS]. **(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]]. **(SAMPLING TECH)** (STRESS) [INTENTIONAL, STRATIFIED]. **(BALANCING AND LABELING)** BP(SBP, DBP) [LABELING].
Ritz et al. (Ritz et al., 2000)	(HR, BP(SBP, DBP), ROS, RR, VT, EDA, EMOTIONS) [ANOVA].	**(RED. DIM. AND RED. OBJS.)** (BP(SBP)) [CORRELATION]. **(SEC. AND GER. SIGNAL)** (BP(SBP)) [INTERVALSPLIT].

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

4.5. ANALYSIS

This section summarizes the pre-processing techniques identified in the literature under review.

Data cleaning and preparation is a crucial research topic in various areas of computer science, and can account for a large part of the processing burden of systems (S. Zhang et al., 2010). The existence of data problems can lead to: i) the hiding of useful and interesting patterns from the data; ii) the low performance of algorithms; and iii) inefficient (i.e. low quality) results (S. Zhang et al., 2010). One of the most important requirements of systems where machine learning algorithms are used is the ability to handle imperfect datasets (Gama et al., 2012). Pre-processing is important because it adds quality to RAW data, preparing it for the next processing phase (S. Zhang et al., 2010). The order of application of the techniques is not pre-established, and the input of one technique can be the output of another previously applied in the same system on the same data (Gama et al., 2012).

Pre-processing techniques aim to mitigate the factors that may condition the performance of the algorithms (e.g. removal of noise and imperfections in the data; data conversion, normalization and segmentation; etc.) (Gama et al., 2012). In the literature under review, the techniques most used by researchers are those related to data normalization, filtering, and segmentation, evidencing the researchers' concern with the quality of the data to be subjected to algorithmic processing. However, researchers also make much use of techniques related to the dimensional reduction of the dataset and to the initial treatment of the data (i.e. noise removal, treatment of incomplete or inconsistent data).

Of note is the need for the processing of data originating from the physiological context. Obtaining a good quality physiological data dataset is vital for the development of a good emotional recognition system (K. H. Kim et al., 2004). Physiological RAW data is always contaminated with noise (Jerritta et al., 2011). For example, ECG and EMG signals collected on the face, need to be preprocessed with various types of filter (e.g. LPF), and EDA is usually preprocessed with SIGSMOOTH (Rigas, 2007) (Chang, Zheng, & Wang, 2010) (Jerritta et al., 2011).

Although many researchers use techniques for initial data processing, few report the application of pre-processing techniques in data from the social context. The importance of this data for an emotional recognition system makes it necessary to take into account possible problems in the data: receipt of emotionally irrelevant (i.e. noisy) SMS and EMAIL (e.g. advertising); CALL made or received by mistake; incomplete data filling (e.g. role played by visitors or SMS, CALL or EMAIL interlocutors in the social network (e.g. children, parents, co-workers, neighbors, etc.)); etc.

The use of techniques such as TOLERANCE, MANADJUST and MANINSERT may raise questions of validity of the results obtained. However, it is believed to be difficult to investigate such a subjective and intangible topic as people's emotions without considering the existence of a margin for human error. However, it will be important to use control techniques (e.g. RELIABILITY, CONSISTENCY, etc.) in order to ensure the least possible impact on the dataset and, consequently, on the results of the algorithms.

Choosing the best properties to consider of a dataset is key to creating a compact, efficient and accurate classifier (Gilad-bachrach, 2004) (Hoque, Ahmed, Bhattacharyya, & Kalita, 2016). When a small and meaningful set of properties can be isolated even the most basic classifiers achieve good levels of performance (Gilad-bachrach, 2004). In this literature review, there are many researchers who use automatic techniques for dimensional reduction. However, not as many compare the results obtained between various techniques. We believe that a comparative study of efficiency between various feature selection algorithms, testing even other proven methods not present in this review (e.g. Simba (Gilad-bachrach, 2004) (Rigas, 2007), Fuzzy Mutual Information-based Feature Selection Method for Classification (FMIFS-ND)) (Hoque et al., 2016), etc.) could be important to increase the accuracy of an emotional detection system. It is crucial to find the best and smallest subset of properties in the learning phase, capable of predicting the target labels of the best performing classifiers (Gilad-bachrach, 2004).

The increasing complexity of systems results from the diversification of collection devices (Caballe, 2015) and of the data origins (cf. sensors, instruments and EXISTINGDATA). The necessary INTEGRATION of data from different sources increases the need for dataset and signal maintenance (e.g. more noise and incomplete or inconsistent data, higher dimensionality, new redundancies, normalization, etc.). However, the existence of more data can also enrich the dataset content (e.g. it may make it possible to expose previously unknown data patterns, it may allow the generation of new signal that would be impossible to obtain without the integration of new data). In this context, we consider it important to perform an exploratory study of the data to be normalized and segmented, in order to try to discover the hidden knowledge behind the data that can be extracted through the use of segmentation techniques.

The most widely used sampling technique in the literature under review will be SYSTEMATIC. The natural relationship with time-series type datasets makes this method one of the most suitable to use in a system that relies on time-oriented context data collection. While it seems logical to use this sampling technique, we do not rule out combining it with STRATIFIED. Stratified selection of objects may be appropriate considering the possibility of multiple dimensions or contexts of collection: in the presence of different social network members (e.g. parents, children, co-workers, neighbors, etc.); in a given environment, place or context (e.g. at the office working, at home resting, doing household chores, having lunch with friends, at a restaurant dinner, praying in church, etc.); etc. Although not used in the investigations of this review, it might be interesting to test progressive sampling where the value of n increases while the algorithm's hit rate also continues to increase (Gama et al., 2012) (IPLeiria, 2009) (Pocinho, 2009). The accidental sampling, also not present in the investigations under analysis, is a non-probabilistic technique in which the objects are selected as they appear. We only considered the hypothesis of using this technique in the initial tests of the system for validation of proper functioning.

Data balancing is an important research topic and can call into question the outcome of algorithms (Lemnaru & Potolea, 2018).. A dataset is unbalanced when the data cluster more in a particular class (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). Although the concern for this topic is not always clear in the research under review, we assign it significant importance because of the impact it can have on the accuracy of the results obtained by classifiers. As a way to mitigate the balancing problem if it exists, we considered redefining the dataset size, either by eliminating objects in the majority class or by naturally or synthetically increasing objects in the minorities (i.e. collecting more context data, or through techniques such as +ARTIFICIALDATA) (Gama et al., 2012). It is our belief that the solution of increasing the number of objects by the natural way is a technique widely used by researchers and, it is just not documented, because of the natural and obvious nature of the solution. Other solutions could be studied to solve the balancing problem: assigning classification costs to each class by defining weights for each class; and inducing an individual classification model for each class individually (e.g. majority and minority class are learned separately) (Gama et al., 2012).

LABELING is heavily used by researchers in this literature review, namely, to add emotional ground-truth information to datasets. However, despite being the most used technique for this purpose, we considered the hypothesis of replacing it using integration with other systems that already recognize emotions with interesting hit rates (e.g. Microsoft Cognitive Services

(Microsoft, 2017b), Affectiva Emotion as a Service (Affectiva Inc.), etc.). However, we may eventually use LABELING to tag data in cases where it is difficult or even impossible to collect it from context (e.g. categorizing the affinity of a visitor or conversation partner (i.e. social network proximity), the alcohol level of a drink ingested, etc.).

RESEARCH	DATASET MAINTENANCE	MAINTENANCE OF SIGNAL	SAMPLING AND META-INFORMATION	OTHER TECHNIQUES
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)	**(RED. DIM. AND RED. OBJS.)** (EMG) [SCATTER, LDA [AGGREGATION]].	**(NORM, AMP, AND FILTER)** (EMG) [BPF, SIGAMP, NORM].		
S. H. Lee et al. (S. H. Lee et al., 2016)	**(NOISE, D. INC. AND INC.)** (FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)) [FAKEDATA].	**(NORM, AMP, AND FILTER)** (EYEBROWS, EYELIDS) [NORM].		(FACS, EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH) [CLUSTERING, SPARSEREP] and (EYEBROWS, EYELIDS) [FINDREGION, CROP]. {HAC}.
Eckert et al. (Eckert et al., 2016)		**(CONV. SINAL)** (EYES, EYEBROWS, NOSE, MOUTH) [GREYSCALE [BINARY]]. **(NORM, AMP, AND FILTER)** (EYES, EYEBROWS, NOSE, MOUTH) [IMGCONTRAST].		(EYES, EYEBROWS, NOSE, MOUTH) [FINDREGION, [GREYSCALE [BINARY [MORPHOPS]]] and (FACS, CAU) [MOTIONDETECT].
Matlovic et al. (Matlovic et al., 2016)		**(SEC. AND GER. SIGNAL)** (EEG) [DWT].		
Gogia et al. (Gogia et al., 2016)	**(NOISE, D. INC. AND INC.)** (EEG) [-EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** (EEG) [-DUPLICATE].		**(BALANCING AND LABELING)** (EEG) [[[-EYEBLINK, -DUPLICATE] [LABELING]] [+ARTIFICIALDATA]].	
Z. Zhang et al. (Z. Zhang et al., 2016)	**(RED. DIM. AND RED. OBJS.)** (HEAD, FACS) [PCA].		**(SAMPLING TECH)** (HEAD, FACS) [RANDOM]. **(BALANCING AND LABELING)** (FACS) [LABELING].	(FACS) [FINDREGION, SI-SSM]. {ZFACE}.
Sano & Eng (Sano & Eng, 2016)	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EDA) [LPF [DY/DX [DISTINCTOBJ]]].	**(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [NORM [DY/DX]]] and (ACC)	**(BALANCING AND LABELING)** (SLEEP, EDA) [LABELING].	(ACC) [MOTIONDETECT].

		[MOTIONDETECT [ADL]].		
Zhao et al. (Zhao et al., 2016)	**(NOISE, D. INC. AND INC.)** (RESP, HR) [-NOISE].	**(NORM, AMP, AND FILTER)** (RESP, HR) [D2Y/DX2 [ZHAO1]] and (RESP) [LPF]. **(SEC. AND GER. SIGNAL)** (RESP, HR) [D2Y/DX2, ZHAO2].		(RESP) [LPF [PEAKDETECT]].
Zenonos et al. (Zenonos et al., 2016)	**(NOISE, D. INC. AND INC.)** (MOOD, EMOTIONS) [TOLERANCE].	**(NORM, AMP, AND FILTER)** (IBI) [NORM]. **(SEC. AND GER. SIGNAL)** (IBI) [BANDS].	**(BALANCING AND LABELING)** (EMOTIONS) [LABELING].	
Basu et al. (Basu et al., 2016)	**(RED. DIM. AND RED. OBJS.)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM [MANSELECT]].	**(NORM, AMP, AND FILTER)** (ECG, HR, PR, RESP(RR), EDA, ST, EMG) [NORM].		{KHRV, WEKA, LABCHART, MATLAB, ORIGIN}.
Aracena et al. (Aracena et al., 2016)	**(NOISE, D. INC. AND INC.)** (PUPIL, GAZE) [-NOISE, -EYEBLINK, -SACCADE].	**(NORM, AMP, AND FILTER)** (PUPIL) [LPF, NORM].	**(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].	
Adams & Robinson (Adams & Robinson, 2015)		**(NORM, AMP, AND FILTER)** (FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)) [NORM].		(GAZE) [FINDREGION].
Turan et al. (Turan et al., 2015)	**(RED. DIM. AND RED. OBJS.)** (FACE, EYES) [SLPP, DCC].		**(BALANCING AND LABELING)** (FACE, EYES) [LABELING].	(EYES) [FINDREGION].
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)		**(CONV. SINAL)** (SPPECH) [FOURIER]. **(NORM, AMP, AND FILTER)** (SPPECH) [SIGAMP]. **(SEC. AND GER. SIGNAL)** (SPEECH) [[FOURIER, SIGAMP] [INTERVALSPLIT, DY/DX, D Y/DX^{22}]].		
Lalitha et al. (Lalitha et al., 2015)		**(SEC. AND GER. SIGNAL)** (SPEECH) [DWT].		
Singh et al. (Singh et al., 2015)		**(CONV. SINAL)** (SHOULDERS, HANDS) [VIDEO-PICS]. **(SEC. AND GER. SIGNAL)**		

		(SHOULDERS, HANDS) [VIDEO-PICS [-IMGBKG]].		
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)	**(NOISE, D. INC. AND INC.)** (ECG, ICG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA) [MURALI].	**(NORM, AMP, AND FILTER)** (ECG, EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (ECG, ICG) [SIGSPLIT].		(ECG) [PEAKDETECT].
Jaques et al. (Jaques et al., 2015)	**(NOISE, D. INC. AND INC.)** (EDA) [LPF [NORM [-**PEAK]]]**, (SCREEN) [DISCARDDATA], (EDA, ST, ACC) [MITIGATION] and (LOCAL) [INTEGRATION [FAKEDATA, NULL]]. **(RED. DIM. AND RED. OBJS.)** (EDA, ST, ACC, SLEEP, NAP, STRESS, HEALTH, ENERGY, ALERT, CALM, HAPPY, LOCAL, SCREEN, CALL, SMS, SOCIAL, ACADCL, ACADST, PHYSI, ACADEX, CAFFEI, ALCOH DRUGS) [WFS, MANSELECT].	**(NORM, AMP, AND FILTER)** (EDA) [LPF [NORM]] and <ACC> [NORM]. **(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION [FAKEDATA, NULL] [PATHSTAKEN]] and (EDA) [DY/DX].	**(BALANCING AND LABELING)** (HAPPY) [LABELING].	
Cruz et al. (Cruz et al., 2015)		**(NORM, AMP, AND FILTER)** (EOG) [GMP]. **(SEC. AND GER. SIGNAL)** (EOG) [INTERVALSPLIT].		
Saha et al. (Saha et al., 2014)		**(CONV. SINAL)** (HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [VIDEO-PICS]. **(SEC. AND GER. SIGNAL)** (HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN) [-IMGBKG].		
Matiko et al. (Matiko et al., 2014)	**(RED. DIM. AND RED. OBJS.)** (EEG) [SCATTER, FDA].	**(NORM, AMP, AND FILTER)** (EDA) [FDA [NORM]].	**(BALANCING AND LABELING)** (EDA) [LABELING].	
Bogomolov et al. (Bogomolov et al., 2014)	**(RED. DIM. AND RED. OBJS.)** (PERSON, STRESS, CALL, SMS, PROXIMITY, WEATHER)	**(NORM, AMP, AND FILTER)** (PERSON, STRESS, CALL, SMS,		

	[CORELATION, BOGOMOLOV [MANSELECT]].	PROXIMITY, WEATHER) [NORM].		
Agrawal et al. (Agrawal et al., 2013)		**(CONV. SINAL)** (EYES, MOUTH, LIPS, SKIN) [VIDEO-PICS].		(SKIN, EYES, MOUTH) [FINDREGION]. {MATLAB}.
Soleymani et al. (Soleymani et al., 2013)	**(NOISE, D. INC. AND INC.)** (EMOTIONS) [DISCARDDATA] and (EEG) [-NOISE].	**(CONV. SINAL)** (EEG) [FOURIER]. **(NORM, AMP, AND FILTER)** (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG) [NORM]. **(SEC. AND GER. SIGNAL)** (EEG) [BANDS], (HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH) [NORM] <DISTANCE> [DY/DX] and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [INTEGRATION].	**(SAMPLING TECH)** [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH, EEG, EMOTIONS] [SYSTEMATIC]. **(BALANCING AND LABELING)** (EMOTIONS) [LABELING].	{FEELTRACE}.
Vermun et al. (Vermun et al., 2013)		**(CONV. SINAL)** (HEAD, LIPS, MOUTH, EYEBROWS, ARMS, SHOULDERS, HIP and KNEES) [VIDEO-PICS].		
Kusserow et al. (Kusserow et al., 2013)		**(SEC. AND GER. SIGNAL)** (ACC) [TASKSPLIT] and (HR, ACC) [INTEGRATION].		
Alzoubi et al. (Alzoubi et al., 2013)	**(RED. DIM. AND RED. OBJS.)** (ECG(HRV), RESP, EDA, EMG) [X^2].		**(BALANCING AND LABELING)** (ECG(HRV), RESP, EDA, EMG) [SPREADSUBSAMPLE].	{AUBT}.
Nawasalkar et al. (Nawasalkar et al., 2013)		**(CONV. SINAL)** (NIBP, RESP(RR)) [HHT].		
Sano & Picard (Sano & Picard, 2013b)	**(RED. DIM. AND RED. OBJS.)** <EDA, ACC, PERSON, SLEEP, NAP, HEALTH, MOOD, ALERT, TIRED, LOCAL, SCREEN, ELECTR, CALL, SMS, ALCOH, CAFFEI, STRESS> [CORRELATION, PCA, SFFS].	**(NORM, AMP, AND FILTER)** (EDA) [LPF]. **(SEC. AND GER. SIGNAL)** (EDA) [LPF [DY/DX]] and (ACC) [ADL].		(EDA) [[LPF [DY/DX [PEAKDETECT]]]].

Raudonis (Raudonis, 2013)		**(CONV. SINAL)** (PUPIL) [GREYSCALE].		(PUPIL) [FINDREGION, RAUDONIS2].
Kawai et al. (Kawai et al., 2013)	**(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER> [MANADJUST, -NOISE, MITIGATION].	**(CONV. SINAL)** (PUPIL) [BINARY]. **(NORM, AMP, AND FILTER)** (PUPIL) <DIAMETER> [KAWAI2 [NORM]].		(PUPIL) [FINDREGION, CLUSTERING, KAWAI1].
Babiker et al. (Babiker et al., 2013)	**(NOISE, D. INC. AND INC.)** (PUPIL) [MITIGATION], <PUPIL> [NORM [[-NOISE, -OUTLIERS][FAKEDATA, DISCARDDATA]]]	**(NORM, AMP, AND FILTER)** <PUPIL> [NORM]. **(SEC. AND GER. SIGNAL)** (PUPIL) <INTERVALSPLIT>.	**(SAMPLING TECH)** (PUPIL) [SYSTEMATIC].	(PUPIL) [FINDREGION].
LikamWa et al. (LiKamWa et al., 2013)	**(NOISE, D. INC. AND INC.)** (MOOD) [RELIABILITY, CONSISTENCY]. **(RED. DIM. AND RED. OBJS.)** <MOOD, CALL, EMAIL, SMS, APPS, BROWSER, LOCAL> [SFS, CORRELATION].	**(NORM, AMP, AND FILTER)** (CALL, SMS, EMAIL) <COUNT> [NORM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM [NORM]] and (APPS) [LABELING] <COUNT, DURATION> [NORM]. **(SEC. AND GER. SIGNAL)** (MOOD) [[RELIABILITY, CONSISTENCY] [INTERVALSPLIT]].	**(BALANCING AND LABELING)** (MOOD) [[RELIABILITY, CONSISTENCY]] [INTERVALSPLIT]] <PERIODS <COUNT, STD <MEAN, MAX>>> [LABELING] and (APPS) [LABELING].	(CALL, SMS, EMAIL) [HISTOGRAM], (APPS, BROWSER, LOCAL) <USUAL> [HISTOGRAM], (APPS) <DURATION> [HISTOGRAM] and (APPS) [LABELING] <COUNT, DURATION> [HISTOGRAM].
Murad & Malkawi (Murad & Malkawi, 2012)		**(SEC. AND GER. SIGNAL)** (EEG, HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS].	**(BALANCING AND LABELING)** (HR, HRV, PEP, SV, EDA, RESP(VT, ROS, RR), NSRR, ST) [BANDS [LABELING]].	
C. Y. Chang et al. (Chang et al., 2012)	**(NOISE, D. INC. AND INC.)** (ECG, PR, BVP, EDA) [[LPF, HPF] [-NOISE]]. **(RED. DIM. AND RED. OBJS.)** (ECG, PR, BVP, EDA) [MANSELECT].	**(NORM, AMP, AND FILTER)** (ECG, PR, BVP, EDA) [LPF, HPF, NORM]. **(SEC. AND GER. SIGNAL)** (ECG, PR, BVP, EDA) [R-R].	**(SAMPLING TECH)** (EDA) [SYSTEMATIC] and (BVP, PR) [R-R [SYSTEMATIC]].	(ECG, BVP, PR) [PEAKDETECT].
Bauer & Lukowicz (Bauer & Lukowicz, 2012)		**(SEC. AND GER. SIGNAL)** (LOCAL) [INTEGRATION, USUALPLACES].		
Yang & Bhanu (S. Yang & Bhanu, 2011)		**(CONV. SINAL)** (HEAD, FACE) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (HEAD, FACE) [VIDEO-PICS [IMGALIGN]].		(HEAD, FACE) [FINDREGION, YANG1].

Dhall et al. (Dhall et al., 2011)	**(RED. DIM. AND RED. OBJS.)** (FACE) [VIDEO-PICS [-FRAMES [PCA]].	**(CONV. SINAL)** (FACE) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (FACE) [VIDEO-PICS [NORM]].		(FACE) [VIDEO-PICS [FINDREGION, CROP, NORM [CLUSTERING]]].
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	**(NOISE, D. INC. AND INC.)** (PUPIL) [-NOISE, -EYEBLINK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HRV), PPG, PUPIL> [GA].	**(CONV. SINAL)** (PUPIL) [VIDEO-PICS]. **(NORM, AMP, AND FILTER)** (PUPIL) [IMGSIZE, IMGINTENSITY]. **(SEC. AND GER. SIGNAL)** (ECG(HRV)) [BANDS].		(PUPIL) [FINDREGION, BLINKDETECT].
Hernandez et al. (Hernandez et al., 2011)	**(NOISE, D. INC. AND INC.)** (EDA) [-NOISE].	**(NORM, AMP, AND FILTER)** (EDA, STRESS) [NORM] and <EDA, STRESS> [NORM].	**(BALANCING AND LABELING)** (CALL) [LABELING].	(EDA) [PEAKDETECT].
N. Lane et al. (N. Lane et al., 2011)	**(NOISE, D. INC. AND INC.)** (SLEEP, PHYSI) [MANINSERT].	**(SEC. AND GER. SIGNAL)** (ACC) [ADL].		(SLEEP) [LANE1] and (SLEEP, PHYSI) [MANADJUST].
H. Wang et al. (H. Wang et al., 2010)	**(NOISE, D. INC. AND INC.)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY [-NOISE]]]]]. **(RED. DIM. AND RED. OBJS.)** <EYES> [ADABOOST].	**(NORM, AMP, AND FILTER)** (EYES) [-IMGBKG [NORM [IMGSIZE [IMGINTENSITY]]]]. **(SEC. AND GER. SIGNAL)** (EYES) [-IMGBKG].	**(BALANCING AND LABELING)** (EYES) [+ARTIFICIALDATA, LABELING].	(EYES) [FINDREGION, CROP, COLORCORR].
Bos (Bos, 2010)	**(NOISE, D. INC. AND INC.)** (EEG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <EEG> [PCA].	**(CONV. SINAL)** (EEG) [-NOISE [BPF [FOURIER]]]. **(NORM, AMP, AND FILTER)** (EEG) [-NOISE [BPF]. **(SEC. AND GER. SIGNAL)** (EEG) [-NOISE [BPF [FOURIER [BANDS]]]].		{EEGLAB}.
Y. Liu et al. (Y. Liu et al., 2010)		**(CONV. SINAL)** (EEG) [FD] and [EMOTIONS] [2D-DISCRETE]. **(NORM, AMP, AND FILTER)** <EEG> [GMP]. **(SEC. AND GER. SIGNAL)** <EEG> [INTERVALSPLIT].		
Setz et al. (Setz et al., 2010)	**(NOISE, D. INC. AND INC.)** (EDA) [DISCARDDATA, MANADJUST [-NOISE]].	**(NORM, AMP, AND FILTER)** (EDA) [SIGAMP, LPF [HPF [LPF]]]		(EDA) [PEAKDETECT].

	(RED. DIM. AND RED. OBJS.) <EDA> [WFA].			
J. Kim & Andre (J. Kim & André, 2008)	**(NOISE, D. INC. AND INC.)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV), RESP(RR, BRV), EDA, EMG> [SBS].	**(CONV. SINAL)** (ECG(HR, HRV)) [FOURIER]. **(NORM, AMP, AND FILTER)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [ABPF, LPF] and (EDA, EMG) [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV), RESP(RR, BRV), EDA, EMG) [INTERVALSPLIT], (ECG(HR, HRV), RESP (RR, BRV)) [FOURIER [BANDS]] and (EDA) [NORM [LPF [DY/DX, D2Y/DX2]]].		(ECG(HR, HRV)) [PEAKDETECT].
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	**(NOISE, D. INC. AND INC.)** (RESP) [-PEAK]. **(RED. DIM. AND RED. OBJS.)** <ECG(HR, HRV, IBI), RESP(RR, RDEP), EDA, ST, EMG> and (EMOTIONS) [CORRELATION, MANSELECT].	**(NORM, AMP, AND FILTER)** (EDA) [LPF].	**(BALANCING AND LABELING)** (RESP(RR)) <AMP> [LABELING].	
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	**(NOISE, D. INC. AND INC.)** (PUPIL) [FAKEDATA].	**(NORM, AMP, AND FILTER)** (PUPIL, EDA) [NORM].		
Gunes & Piccardi (Gunes & Piccardi, 2007)	**(RED. DIM. AND RED. OBJS.)** (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-FRAMES] and (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BESTFIRST].	**(CONV. SINAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST [BINARY]] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [BINARY]. **(NORM, AMP, AND FILTER)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [IMGCONTRAST] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK)		(LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW, SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [MORPHOPS, FINDREGION]. {WEKA}.

		[IMGSIZE, IMGCONTRAST]. **(SEC. AND GER. SIGNAL)** (LIPS, MOUTH, EYES, EYEBROWS, EYELIDS, NOSE, CHEEKS, FOREHEAD, JAW) [COLORSEG] and (SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK) [-IMGBKG].		
Castellano et al. (Castellano et al., 2007)	**(RED. DIM. AND RED. OBJS.)** (ARMS) [DISCARDDATA].	**(NORM, AMP, AND FILTER)** (ARMS) <MOTION <MAX, MIN>> [NORM]. **(SEC. AND GER. SIGNAL)** (ARMS) [-IMGBKG].		{EYESWEB}.
Mandryk & Atkins (Mandryk & Atkins, 2007)	**(NOISE, D. INC. AND INC.)** (ECG(HR)) [MANADJUST, FAKEDATA].	**(NORM, AMP, AND FILTER)** (ECG(HR)) [FAKEDATA [SIGSMOOTH [NORM]]], (EMG) [SIGSMOOTH [NORM]] and (EDA) [BPF [NORM]]. **(SEC. AND GER. SIGNAL)** (ECG(HR), EDA, EMG) and {VIDEO, AUDIO} [INTEGRATION].	**(SAMPLING TECH)** (ECG(HR)) [SYSTEMATIC], (ECG(HR), EDA, EMG) [STRATIFIED]. **(BALANCING AND LABELING)** (ECG(HR), EDA, EMG, EMOTIONS) [LABELING].	(ECG(HR), EDA, EMG) [HISTOGRAM].
Sebe et al. (Sebe et al., 2006)	**(RED. DIM. AND RED. OBJS.)** (PITCH) [CORRELATION].	**(CONV. SINAL)** (HEAD, EYEBROWS, EYELIDS, MOUTH) [3D2D]. **(SEC. AND GER. SIGNAL)** (HEAD, EYEBROWS, EYELIDS, MOUTH, VOLUME, SPEECH, PITCH) [INTEGRATION].		
Zhai & Barreto (Zhai & Barreto, 2006)	**(NOISE, D. INC. AND INC.)** (PUPIL) <DIAMETER>[-NOISE [FAKEDATA]].	**(NORM, AMP, AND FILTER)** (ST) [SIGAMP [LPF [NORM]]] and (BVP(IBI), EDA) [NORM].		
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	**(NOISE, D. INC. AND INC.)** (EDA, ECG(HR, HRV)) [DISCARDDATA] and (STRESS) [RELIABILITY]. **(RED. DIM. AND RED. OBJS.)**	**(NORM, AMP, AND FILTER)** (STRESS, EMG, RESP, ECG(HR), EDA) [NORM] and (EMG) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)**	**(BALANCING AND LABELING)** (STRESS) [LABELING].	(EDA) [PEAKDETECT].

	<EDA, EMG, RESP, ECG(HR, HRV)> [SCATTER, MANSELECT].	(ECG(HR, HRV), RESP, EDA, EMG) and {VIDEO} [INTEGRATION], (ECG(HR, HRV), RESP, EDA, EMG) [INTERVALSPLIT] and (RESP) [BANDS].		
Herbon et al. (Herbon et al., 2005)	**(NOISE, D. INC. AND INC.)** (HR, EDA, PUPIL, EMOTIONS) [DISCARDDATA] and (HR, EDA, PUPIL) <STD <THRESHOLD>> [DISCARDDATA].	**(CONV. SINAL)** (HR, EDA, ST, PUPIL) [ZTRANSFORM].		
Partala et al. (Partala et al., 2005)	**(NOISE, D. INC. AND INC.)** (EMG) [-EYEBLINK].	**(NORM, AMP, AND FILTER)** (EMG) [SIGAMP [HPF, LPF]]. **(SEC. AND GER. SIGNAL)** (EMG) and (EMOTIONS) [LABELING].		(EMG) [TTEST].
Van Eck et al. (van Eck et al., 2005)	**(NOISE, D. INC. AND INC.)** (HEALTH) [DISCARDDATA] and (CORT) [-OUTLIERS]. **(RED. DIM. AND RED. OBJS.)** (LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS, PHYSI, SMOKING, FOOD, CAFFEI, ALCOH) [PCA [AGGREGATION]]].		**(BALANCING AND LABELING)** (STRESS) [LABELING].	
Busso et al. (Busso et al., 2004)	**(RED. DIM. AND RED. OBJS.)** <PITCH, VOLUME> [SBS], <FOREHEAD, EYEBROWS, EYES, CHEEKS> [PCA] and <PITCH, VOLUME, FOREHEAD, EYEBROWS, EYES, CHEEKS> [SBS [AGGREGATION], MANSELECT].			(FOREHEAD, EYEBROWS, EYES, CHEEKS) [FINDREGION, CLUSTERING].
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		**(NORM, AMP, AND FILTER)** (HR, EDA, ST) [NORM].		
K. H. Kim et al.	**(NOISE, D. INC. AND INC.)**	**(NORM, AMP, AND FILTER)**	**(SAMPLING TECH)**	(ECG(HR, HRV)) [PEAKDETECT].

(K. H. Kim et al., 2004)	(ECG(HR, HRV)) [PEAKDETECT [R-R [FAKEDATA]]] and (ECG(HRV), EDA) [THRESHOLD [-OUTLIERS]].	(EDA) [SIGAMP, GMP] and (ECG(HR, HRV), EDA, ST, PPG) [NORM, SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (ECG(HR, HRV)) [PEAKDETECT [R-R]], (ECG(HRV)) [BANDS] and (EDA) [INTERVALSPLIT].	(ECG(HRV), EDA) [DECIMATION].	
Haag et al. (Haag et al., 2004)		**(NORM, AMP, AND FILTER)** (ECG(HR) [LPF [HPF]], (ECG(HR) [[DY/DX, D2Y/DX2] [SIGSMOOTH]], (EDA) [NORM [LPF]], (EMG) [SIGSMOOTH] and <PPG(BVP(HR)), ECG, RESP, EDA, ST, EMG> [NORM]. **(SEC. AND GER. SIGNAL)** (ECG(HR)) [DY/DX, D2Y/DX2] and (PPF(BVP(HR)), RESP) [INTERVALSPLIT].		(PPG(BVP(HR))) [HISTOGRAM].
Partala & Surakka (Partala & Surakka, 2003)	**(NOISE, D. INC. AND INC.)** (PUPIL) [DISCARDDATA, -EYEBLINK].		**(BALANCING AND LABELING)** (PUPIL) [LABELING].	(PUPIL) [PEAKDETECT, TTEST].
C J Harmer et al. (C J Harmer et al., 2003)	**(RED. DIM. AND RED. OBJS.)** (MOOD, ENERGY) [PCA].			
Nwe et al. (Nwe et al., 2001)		**(CONV. SINAL)** (SPEECH) [FOURIER]. **(NORM, AMP, AND FILTER)** (SPEECH) [SIGSMOOTH]. **(SEC. AND GER. SIGNAL)** (SPEECH) [INTERVALSPLIT].		
Buchanan & Lovallo (Buchanan & Lovallo, 2001)			**(BALANCING AND LABELING)** (EMOTIONS) [LABELING].	
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)		**(CONV. SINAL)** (RESP) [FOURIER]. **(NORM, AMP, AND FILTER)** (PPG(BVP(HR)), ECG(HR, HRV), RESP,	**(BALANCING AND LABELING)** (EMG) [LABELING].	{MATLAB}.

		EDA) [SIGSMOOTH, NORM].		
Vrijkotte et al. (Vrijkotte et al., 2000)	**(NOISE, D. INC. AND INC.)** (BP(SBP, DBP)) [-NOISE, -OUTLIERS].	**(SEC. AND GER. SIGNAL)** (PHYSI, ECG(HR, HRV, IBI(RMSSD(VAGAL))), ACC) [INTEGRATION [ADL]].	**(SAMPLING TECH)** (STRESS) [INTENTIONAL, STRATIFIED]. **(BALANCING AND LABELING)** BP(SBP, DBP) [LABELING].	[AGE, BMI, WAIST, SMOKING, ALCOH, ACADDG, WORKYEARS, PHYSI, MOOD] [ANOVA]. {GLM}.
Ritz et al. (Ritz et al., 2000)	**(RED. DIM. AND RED. OBJS.)** (BP(SBP)) [CORRELATION].	**(SEC. AND GER. SIGNAL)** (BP(SBP)) [INTERVALSPLIT].		(HR, BP(SBP, DBP), ROS, RR, VT, EDA, EMOTIONS) [ANOVA].
L. S. Chen et al. (L. S. Chen et al., 1998)	**(NOISE, D. INC. AND INC.)** (EYES, EYEBROWS, MOUTH, WRINKLES, FROWN) [MANINSERT].	**(CONV. SINAL)** (EYES, MOUTH) [FOURIER]. **(NORM, AMP, AND FILTER)** (PITCH) [NORM]. **(SEC. AND GER. SIGNAL)** (SPEECH) [INTERVALSPLIT] and (PITCH) <CONTOUR> [DY/DX].		
J. Healey & Picard (J. Healey & Picard, 1998)		**(NORM, AMP, AND FILTER)** (RESP) [NORM], <RESP> [NORM] and (EDA) [SIGSMOOTH, NORM].	**(BALANCING AND LABELING)** (EMG, EDA, PPG(BVP(HR)), RESP) [LABELING].	
Rajita Sinha (Rajita Sinha, 1996)	**(NOISE, D. INC. AND INC.)** (BP(DBP)) [DISCARDDATA] and (EMG) [-NOISE]. **(RED. DIM. AND RED. OBJS.)** (EMG) [MANSELECT].	**(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, BPF, NORM], (ST) [SIGAMP] and (ECG(HR), BP(SBP, DBP), EDA, EOG) [NORM].	**(SAMPLING TECH)** (EMG, ST) [SYSTEMATIC].	
Scott R. Vrana (Scott R. Vrana, 1993)	**(NOISE, D. INC. AND INC.)** (ECG(HR)) [DISCARDDATA].	**(CONV. SINAL)** (EMOTIONS) [QUALI-QUANTI]. **(NORM, AMP, AND FILTER)** (EMG) [SIGAMP, LPF, HPF].		
R Sinha et al. (R Sinha et al., 1992)	**(NOISE, D. INC. AND INC.)** (ICG(SV, CO, PVR, PEP, LVET)) [MANINSERT] and (ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)) [DISCARDDATA]. **(RED. DIM. AND RED. OBJS.)**	**(NORM, AMP, AND FILTER)** (ECG(HR)) [SIGAMP]. **(SEC. AND GER. SIGNAL)** (ECG) [R-R].		

	(BP(SBP, DBP), ECG(HR)) [MANSELECT].			

() represents a raw signal; {} an instrument; [] a preprocessed signal, and <> an extracted property.

5. EXTRACTED PROPERTIES

The accuracy of the algorithms depends on the quality of the input properties of the system (Matlovic et al., 2016), making their choice an important step for classification algorithms (Adams & Robinson, 2015). Properties can be extracted directly from the signal collected by instruments and sensors (i.e. RAW) or from any output resulting from the application of pre-processing techniques. Properties are most appropriate to the classification process and can be viewed as complementary or replacement inputs to the attributes of the original dataset (Haag et al., 2004). After pre-processing it is necessary to define which statistical measures or properties are optimal for emotional recognition to extract from the signal (Jerritta et al., 2011). For e.g. Kim & André, based on raw ECG, EMG, EDA and RESP signals, extracted various properties from the preprocessed signal for the time domain, and frequency domain (J. Kim & André, 2008).

In this literature review we identified four categories of properties: domain; context-specific; mathematical and signal analysis; and the generic. The **domain properties** were identified in the section on context variables, due to the fact that the method of obtaining them is confusable with that used in the collection itself. As the literature analyzed also does not formally distinguish them from the context variables and they are, in some cases, automatically determined by the collection instruments themselves, we decided to also consider them in the section 2 (context variables) (e.g. the IBI used by Zenonos et al. was provided directly by SILMEEW2X without the need for any pre-processing (Zenonos et al., 2016); the HRV is a property extracted from the ECG, however, some devices provide it directly (Lichtenstein, Antje; Oehme, 2008.); etc.). **Context-specific properties**, which increase the variety and quality of input from systems (Matlovic et al., 2016) are the subject of analysis in this section. Since they are dependent on the context from which they are extracted, it was decided to divide this section according to the original context variables. The **mathematical and signal analysis properties**, and the **generic properties,** although widely referenced by the literature, are not addressed in detail in this paper as we consider them to be general knowledge. They are, however, summarized below because they are referenced in the various texts in this section.

Statistical measures allow the extraction of properties related to the organization, characterization, and analysis of data. In this bibliographic survey, the following were identified: measures of central tendency; measures of dispersion; and measures of distribution.

<u>Measures of central tendency</u> are widely used by researchers (e.g. Lang et al. (Peter J. Lang, Levin, Miller, & Kozak, 1983), Miller et al. (Miller et al., 1987), etc.)) (Rajita Sinha, 1996). Measures of central tendency are used in various realities (e.g. in preventing the impact of outliers on the signal) (Rajita Sinha, 1996). There are several measures of central tendency used by research under review: mean **<MEAN>** to indicate the midpoint of numerical values; median **<MEDIAN>** which represents the center point of the data distribution; the **<MODE>** which represents the most frequent value in a distribution; mean of absolute values **<MAV>** (also known as Averaged Absolute Value or Average Rectified Value) (Phinyomark et al., 2012); MAV

weighed by windows functions <MAVS> (Phinyomark et al., 2012); average of the absolute values of the first difference <MAV1D> (Basu et al., 2016) (R.W. Picard, Vyzas, & Healey, 2001); mean of the absolute values of the second difference **<MAV2D>** (Basu et al., 2016) (R.W. Picard et al., 2001); and the quantile **<QUANTILE**>. Researchers also use measures of dispersion to analyze the variability of values in a dataset. In the literature reviewed, the following measures of dispersion were identified: variance **<VAR**>; standard deviation **<STD**>; absolute deviation **<AD>;** amplitude **<AMP**>; maximum **<MAX**>; minimum **<MIN**>; and covariance **<COVAR>** which allows the analysis of the dispersion between two or more attributes (Gama et al., 2012). These measures are calculated over all or parts of the signal (e.g. Sano & Eng. calculated the average AMP of the signal collected by several electrodes (Sano & Eng, 2016)). Distribution measures allow characterizing the arrangement of the data represented in a histogram. In the literature reviewed, the following measures were identified: skewness **<SKEWNESS>** which measures the symmetry of the distribution around the mean; and kurtosis **<KURTOSIS>** which represents the flattening of the distribution function (Gama et al., 2012) (Korkmaz & Atasoy, 2015).

Geometric measurements are related to spatial sense, shape, dimensions of surfaces, volumes, etc. (e.g. shapes, perimeters, radius, diameters, angles, distances, volumes, lengths, widths, heights, etc.). There are several researchers who use geometry in their research: Gogia et al. used pitch, yaw and roll, to represent the **<ANGLE>** angles of HEAD on the vertical, horizontal and horizontal axis without turning the neck (Gogia et al., 2016); Mokhayeri et al. calculated the diameter **<DIAMETER>** of the PUPIL (Mokhayeri & Toosizadeh, 2011); Sano et al. calculated the approximate **<RADIUS>** radius of movement of participants in their experiment (Sano & Picard, 2013b); Eckert et al. calculated the **<AREA>** area of SHAPE recognized (Eckert et al., 2016); Jaques et al. determined the traveled distances **<DISTANCE>** based on the LOCAL data throughout the day (Jaques et al., 2015) (Lee et al. also calculated DISTANCE between face zones (e.g. EYEBROWS and EYELIDS) (S. H. Lee et al., 2016) and Eckert et al. calculated the DISTANCE between points (e.g. from a SHAPE (Eckert et al., 2016))); slope **<SLOPE>** (e.g. Singh et al. used the SLOPE of SHOULDERS to predict people's emotional state (Singh et al., 2015)); size **<SIZE>** (e.g. Sano & Picard and LikamWa et al. used SMS size as an extracted property (Sano & Picard, 2013b) (LiKamWa et al., 2013)); and the centroid **<CENTROID>** in determining the geometric center of clusters (S. H. Lee et al., 2016). Some authors perform the identification of **<SHAPE>** patterns formed by connector lines between groups of points (e.g. Lee et al. (S. H. Lee et al., 2016.)): Eckert et al. performed pattern recognition to evaluate the triangle formed by the point groups of EYES and EYEBROWS (Eckert et al., 2016); Zhang et al. used Active Shape Model to detect the SHAPE of the face (Cootes, Taylor, Cooper, & Graham, 1995) (Z. Zhang et al., 2016); etc.

From the **signal analysis** it becomes possible to extract various properties in the time and frequency domain. The extraction of properties from the signal in the time domain has also been widely used in medicine and engineering, perhaps because it does not involve background transformations to the signal collected by instruments and sensors (Phinyomark et al., 2012) (Hudgins, Parker, & Scott, 1993). There are several properties extracted from the analysis from the time domain: the Waveform Length **<WL>** measures the complexity of a signal (e.g. Phinyomark et al. (Phinyomark et al., 2012)); the Willison Amplitude **<WAMP>** represents the amount of times the difference between two adjacent signal segments exceeds a predefined threshold (Phinyomark et al., 2012); the Auto-Regressive **<AR>** describes each signal sample as a combination of several samples (Phinyomark et al., 2012). The properties of the spectrum or frequency domain are widely used by researchers, with Power (Energy) Spectral Density **<PSD>**

being one of the most widely used analyses and showing the distribution of the VAR in function of frequency (Zenonos et al., 2016) (Phinyomark et al., 2012) (Soleymani et al., 2013). There are several properties extracted from frequency domain analysis: peak frequency **<PKF**>; low frequency peak **<PLF**>; high frequency peak **<PHF>** (e.g. Zhao et al. (Zhao et al., 2016.)); dominant frequency **<DMF>** (e.g. Kim et al. (J. Kim & Andre, 2008)); ratio of low frequency to high frequency **<LF/HF**>; and ratio of the sum of low and medium frequency to high frequency **<LFMF/HF**>.

Other possible properties to extract from the signals were also identified: magnitude **<MAG>** (e.g. Jaques et al. used MAG to detect motion and normalize EDA (using a THRESHOLD the author estimated the number of steps of the user) (Jaques et al., 2015)); root mean square value or effective value **<RMS>** (Root-Mean-Square) (Wikipedia, n.d.) (Weisstein, 2017); power **<POWER>** and strength **<STRENGTH>** (e.g. Matlovic et al. calculated the POWER and STRENGTH of the ALPHA and BETA waves of the (EEG) [DWT] (Matlovic et al., 2016)); main peak of the signal **<MAINPEAK>** (e.g. Catellano et al. (Castellano et al., 2007)); area under the curve of a function **<INTEGRAL>** (e.g. Jaques et al. (Jaques et al., 2015)); signal rise time **<RISETIME>** (e.g. Jaques et al. (Jaques et al., 2015)); the first and second difference values **<1DIFF> <2DIFF>** which are used as approximation to DY/DX and D^2Y/DX^2 (e.g. Alzoubi et al. used 1DIFF and 2DIFF to calculate ratios with EDA, RESP, etc. (Alzoubi et al., 2013)); zero crossings $(y = 0)$ (zero crossings) **<ZEROCROSSINGS>** (e.g. Hernandez et al. (Hernandez et al.)); signal turning points **<TPOINTS>** (e.g. Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)); and signal or data variation or change **<CHANGES>** (e.g. increase or decrease in size, diameter, HR acceleration or deceleration) (e.g. Bradley et al. (Margaret M. Bradley et al., 2008), Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008), Healey et al. (J. Healey & Picard, 1998), and Vrana (Scott R. Vrana, 1993)).

Researchers also use another type of analysis to extract properties: poincaré plots **<POINCARE>** which allows to visually assess the similarity of data (A. C. C. Yang, 2006) (Kamen, Krum, & Tonkin, 1996) (e.g. Zenonos et al. used POINCARE to analyze the similarities of the current IBI with previous ones, assuming the assumption that the current IBI is influenced by the previous one (Zenonos et al., 2016)); entropy measures used to assess time series complexity **<ENTROPY>** (spectral entropy, sample entropy (SAMPEN), which is a modification of approximate entropy (APEN)) (Aboy, Cuesta-Frau, Austin, & Mico-Tormos, 2007) (Lake, Richman, Griffin, & Moorman, 2002) (Zenonos et al., 2016) (J. Kim & Andre, 2008); and detrend fluctuation analysis **<DFA>** which is based on the concept that a system or shape can be decomposed into several pieces and that each piece resembles the others but at different scales (the goal is to find similar properties in non-stationary time series) (Zenonos et al., 2016) (Penzel, Kantelhardt, Grote, Peter, & Bunde, 2003).

In addition to these properties, **other** more generic mathematical concepts are also used: ratio **<RATIO>** to measure the relationship between values (e.g. Matlovic et al. calculated RATIO between BETA/ALPHA to assess the arousal level of participants in their experience (Matlovic et al., 2016)); number of times **<COUNT>** that a certain action or task occurs; sum of values **<SUM>** (e.g. J. Healey et al. summed the MAG of the segregated EDA signal (J. A. Healey & Picard, 2005)); time spent or duration of one or several tasks or actions **<DURATION**>; grouping of data into time periods or other pre-established criteria (i.e. sets, cycles, etc.) **<PERIODS>** (e.g. daily, 6am-12am, sleep periods, etc.); time elapsed between actions **<ELAPSEDTIME>** (e.g. Bogomolov et al. used the interval between CALL, SMS, and EMAIL (Bogomolov et al., 2014)); latency **<LATENCY**>; displacement **<DISPLACEMENT> (**i.e. amount of displacement that occurred) (e.g. Lee et al. calculated the geometric displacement of face zones between video frames (S. H. Lee et al., 2016)); motion **<MOTION>** (e.g. Vermun et al. used head movements (cf. nodding, shaking, tilting, turning) as properties in their system (Vermun et al., 2013)); speed **<SPEED>** (e.g. Saha et al. calculated SPEED based on the DISPLACEMENT of joints in the upper part of the human body collected by KINECT (Saha et al., 2014)); subtraction of **<SUBTRACT>** data (e.g. Matlovic et al. calculated differences in electrical activity between hemispheres of the brain to assess valence (Matlovic et al., 2016) and Saha et al. calculated SPEED based on the difference (i.e. SUBTRACT) of joint DISPLACEMENT in two consecutive frames); position **<POSITION>** (e.g. Saha et al. used the POSITION of people's upper limbs to infer emotions (Saha et al., 2014), Soleymani et al. used reference points of the EYES and NOSE to correct the POSITION of the HEAD (Soleymani et al., 2013)); intensity **<INTENSITY**>; location **<LOCATION>** (e.g. Raudonis estimated the coordinates of the PUPIL in images (Raudonis, 2013)); direction **<DIRECTION>** (e.g. Adams & Robinson and Aracena et al. used the DIRECTION of GAZE in their investigations (Adams & Robinson, 2015) (Aracena et al., 2016)); correlation (CORRELATION) (e.g. Agrawal et al. used correlation coefficients to assess the change in position of the EYES and LIPS between frames (Agrawal et al., 2013), Soleymani et al. calculated the CORRELATION between EEG signal and face muscle movement to prove the strong interference of muscle activity and eye movements on EEG signal (Soleymani et al., 2013)); and data thresholding to define the point at which a given action or value gains or loses effect **<THRESHOLD> (**e.g. Perdiz et al. used THRESHOLD in the classification of the EOG signal (Perdiz et al., 2017), Eckert et al. used THRESHOLD to assess when there are changes in the UACs (Eckert et al., 2016)).

Also the indication of some generic labels to support categorization: left **<LEFT**>, right **<RIGHT>** and center **<CENTER>** (e.g. Vermun et al. measured the coordinates of the LEFT and RIGHT KNEE and determined the CENTER of the SHOULDER (Vermun et al., 2013)); start **<BEGIN>** and end **<END>** of an action or event; first **<FIRST**>, second **<SECOND>,** third **<THIRD>,** etc. occurrence of an action or event; identification of the moment(s) when an action, collection, or task happens **<TIMING**>; last time an action occurred or a task was performed **<LASTTIME**>; qualitative regularity of a given action or event (e.g. infrequent or very frequent) **<REGULARITY**>; use of objects or devices **<USAGE**>; planned execution of an action or event **<PLANNING**>; reason for an action or event to happen **<WHY**>; quality of something or with which a task or action happens **<QUALITY**>; quantity **<QUANTITY**>; generic measurement level **<LEVEL**>; phases of processes, experiences, or events **<PHASES**>; most usual events, actions, or interactions **<USUAL**>; state of a task, object, or component **<STATUS>** (e.g. Wang et al. used the STATUS of the EYES in their research about fatigue (H. Wang et al., 2010)); and height **<HEIGHT**>.

The following sections use these properties without regard to their mathematical categorization. The organization assumed groups the extracted properties according to the origin of the respective context variables. It is intended to facilitate the reading of the document by emphasizing the **specific properties of the** collection context.

Some context variables may be decomposed into several, for example by being collected by multiple context introspection methods or being composed of several data collected from the context. Thus, this section also breaks down the various original properties (i.e. RAW attributes) that make up and make up the composite context variables. For e.g., to collect the context variable PHYSI, researchers Jaques et al. estimated the number of steps through the ACC and jointly requested the completion of questionnaires about daily physical activity (Jaques et al., 2015). The context variable WEATHER used by Bogomolov et al. is composed of data about ambient temperature (i.e. TEMP), atmospheric pressure, precipitation, humidity, wind, etc. (Bogomolov et al., 2014). Yet another example, Jaques et al. collected the LOCAL variable based on data coming from several sources: GPS coordinates; WiFi signal; and mobile communications operator antenna (Jaques et al., 2015)).

When it is necessary to specify several context variables (i.e. multimodal collection) (e.g. [EDA, SLEEP] (physiological context, and social and psychological context)) the categorization that most closely relates to the nature of the values of the extracted properties will be chosen.

Many of the pre-processing techniques reviewed in the previous section prepare the RAW signal so that it is more suitable to be input to the classification algorithms (Gama et al., 2012). However, some of the techniques derive the RAW into other signals (i.e. generate new signal from the RAW) (e.g. DY/DX, ADL, etc.). In order to simplify the reading of this document, the signal resulting from the application of the pre-processing techniques for signal maintenance (e.g. RAW) will only be referred to as final context data **<FINALRAW**>, with only references to the pre-processing techniques being made when applied to the extracted properties. When referring to a derived signal (i.e. a new signal), the token already assigned will be used to symbolize it. Thus (EDA) [RAW, FINALRAW, DY/DX] <MEAN, MAX> indicates MEAN and MAX properties extracted directly from the EDA RAW signal, MEAN and MAX properties extracted from FINALRAW, and MEAN and MAX properties extracted from the new DY/DX signal. There may also be chaining of extracted properties. For e.g. (LOCAL) [RAW] <<LATITUDE, LONGITUDE><MEDIAN>> represents the MEDIAN property calculated based on the LATITUDE property and the MEDIAN property calculated based on the LONGITUDE property of the RAW signal of the LOCAL context variable.

To simplify the notation and when understandable, the term FINALRAW may be omitted using the square brackets to identify the intended end sign. Thus, following the simplification previously introduced where (EDA) [RAW] would be equivalent to just mentioning (EDA), and (EDA) [FINALRAW] may be represented by just [EDA] assuming the same meaning.

The following table summarizes the various context-specific properties used by the authors of the research analyzed in this literature survey. The mathematical properties already presented will not be explained in this summary table, because they are common knowledge and will not be detailed later.

DESCRIPTION	**ID**	**GROUP** (category)
FACIAL EXPRESSION, ORAL EXPRESSION AND BODY POSTURE		
Brow raising (raising or lowering of the eyebrows)	**BROWSRAISING**	Facial expression and posture
Clusters (image or video)	**CLUSTERS**	Facial expression and posture
Pitch count	**COUNTOUR**	Oral Expression
Crossed arms	**CROSSEDARMS**	Facial expression and posture
DWTC (Discrete Wavelet Transform Coefficients)	**DWTC**	Oral Expression
Erect back	**ERECTBACK**	Facial expression and posture
Eye **corners**	**EYECORNERS**	Facial expression and posture
Finger **tapping**	**FINGERTAPPING**	Facial expression and posture
GABOR (Gabor wavelets)	**GABOR**	Facial Expression
Harmonic to Noise Ratio	**HNR**	Oral Expression
Iris (iris of the eye)	**IRIS**	Facial expression and posture

LBP (local binary pattern)	**LBP**	Facial Expression
Lip bite	**LIPBITE**	Facial expression and posture
Lips pucker	**LIPSPUCKER**	Facial expression and posture
Lip **wipe**	**LIPWIPE**	Facial expression and posture
LPCC (Linear Predictive Cepstral Coefficients)	**LPCC**	Oral Expression
LPQ (local phase quantization)	**LPQ**	Facial Expression
MEDC (Mel Energy Spectral Dynamic Coefficients)	**MEDC**	Oral Expression
MFCC (Mel Frequency Cepstral Coefficients)	**MFCC**	Oral Expression
Mouth **corners**	**MOUTHCORNERS**	Facial expression and posture
Mouth **opening**	**MOUTHOPENING**	Facial expression and posture
Mouth **stretch**	**MOUTHSTRETCH**	Facial expression and posture
PHOG (Pyramid of histogram of oriented gradients)	**PHOG**	Facial Expression
Shimmer	**SHIM**	Oral Expression
Stick pose	**SINGH**	Oral Expression
Sitting **posture**	**SITTINGPOSTURE**	Facial expression and posture
Spectral centroid	**SPCE**	Oral Expression
Spectral flux	**SPFL**	Oral Expression
Spectral roll off	**SPRO**	Oral Expression
TEAE (Teager Energy)	**TEAE**	Oral Expression
WLD (weber local descriptor)	**WLD**	Facial Expression
Wrinkled eyelid	**WRINKLEDEL**	Facial expression and posture
Wrinkled **eyes**	**WRINKLEDEYES**	Facial expression and posture
Wrinkled **forehead**	**WRINKLEDFH**	Facial expression and posture
Wrinkled nose	**WRINKLEDNOSE**	Facial expression and posture
Zero Crossing Rate	**ZCR**	Oral Expression
PHYSIOLOGICAL ENVIRONMENT		
Alpha waves	**ALPHA**	Brain activity
Attention level	**ATTENTION**	Brain activity
Beta waves	**BETA**	Brain activity
Muscle contractions	**CONTRACTIONS**	Muscle activity
Delta waves	**DELTA**	Brain activity
Pupil dilation	**DILATION**	Eye activity
Corrugator supercilli muscle (activity of the...)	**EMGCOR**	Muscle activity
Zygomaticus major muscle	**EMGZYG**	Muscle activity
Eye horizontal movement	**EOGH**	Eye activity
Eye vertical movement	**EOGV**	Eye activity
Eye fixation	**FIXATION**	Eye activity
Frowning	**FROWNING**	Muscle activity
Gamma waves	**GAMMA**	Brain activity
Hemisphere activity (left and right hemisphere activity)	**HEMISPHERE**	Brain activity
Heart Rate Variability Index	**HRVI**	Cardiac activity
Heart Rate Variability Triangular Index	**HRVTI**	Cardiac activity
Levator labii superioris	**LEVATOR**	Muscle activity
Meditation **level**	**MEDITATION**	Brain activity

Muscle (muscle activity)	**MUSCLE**	Muscle activity
pNNx (percentage of N-N intervals that differ by more than x milliseconds)	**PNNX**	Cardiac activity
Eye saccade (quick eye movements)	**SACCADE**	Eye activity
Standard Deviation of N-N intervals	**SDNNI**	Cardiac activity
Smilling (smiling)	**SMILING**	Muscle activity
Muscle **tension**	**TENSION**	Muscle activity
Theta waves (theta waves)	**THETA**	Brain activity
Triangular interpolation of N-N Interval Histogram	**TINN**	Cardiac activity
SOCIAL AND PSYCHOLOGICAL CONTEXT		
Affinity (affinity with the interlocutors)	**AFFINITY**	(used in the variable SOCIAL)
Agreeableness	**AGREEABLENESS**	(used in the variable PERSON)
Answer (calls in response to other calls)	**ANSWER**	(used in CALL, SMS and EMAIL variables)
Awakenings (awakenings during sleep)	**AWAKENINGS**	(used in the variable SLEEP)
Categorical data (qualitative nominal data, ordinal data, scales, etc.)	**CATEGORICAL**	(used in the questionnaires)
Classroom (time spent in physical classrooms)	**CLASSROOM**	(used in variable ACADCL)
Conscientiousness	**CONSCIENTIOUSNESS**	(used in the variable PERSON)
Controllability	**CONTROLLABILITY**	(used in variable STRESS)
Devices (number of devices detected in the vicinity)	**DEVICES**	(used in the variable PROXIMITY)
Effort	**EFFORT**	(used in variable STRESS)
Extraversion	**EXTRAVERSION**	(used in the variable PERSON)
Group work	**GROUPWORK**	(used in variable ACADCL)
Important (importance)	**IMPORTANCE**	(used in variable STRESS)
Incoming (calls, SMS and e-mails received)	**INCOMING**	(used in the CALL, SMS and EMAIL variables)
Iniated only	**INITIATEDONLY**	(used in the CALL, SMS and EMAIL variables)
Interactions (quality of social interactions)	**INTERACTIONS**	(used in the variable SOCIAL)
Interlocutors (number of interlocutors)	**INTERLOCUTORS**	(used in CALL, SMS and EMAIL variables)
Laboratories (time spent in laboratories)	**LAB**	(used in variable ACADCL)
Last stress event	**LASTSTRESS**	(used in variable STRESS)
Latitude (Global Position System...)	**LATITUDE**	(used in the variable LOCAL)
Longitude (Global Position System...)	**LONGITUDE**	(used in the variable LOCAL)
Missed **call**	**MISSEDCALL**	(used in the CALL, SMS and EMAIL variables)
Neuroticism	**NEUROTICISM**	(used in the variable PERSON)
Online class (time spent in virtual classrooms)	**ONLINECLASS**	(used in variable ACADCL)
Openness	**OPENNESS**	(used in the variable PERSON)
Outgoing (outgoing calls, SMS and emails)	**OUTGOING**	(used in CALL, SMS and EMAIL variables)
Overcommitment	**OVERCOMMITMENT**	(used in variable STRESS)
Predictability	**PREDICTABILITY**	(used in variable STRESS)
Reward	**REWARD**	(used in variable STRESS)
Regions of **Interest**	**ROI**	(used in the variable LOCAL)
Seminars (time spent in seminars)	**SEMINAR**	(used in variable ACADCL)
Sleep **conditioners**	**SLEEPCONDITIONERS**	(used in the variable SLEEP)
Sleep **kind**	**SLEEPKIND**	(used in the variable SLEEP)

Unpleasantness	**UNPLEASANTNESS**	(used in variable STRESS)
Wakeup kind	**WAKEUPKIND**	(used in the variable SLEEP)

5.1. FACIAL, ORAL EXPRESSION AND BODY POSTURE

This section includes properties related to the analysis of facial expression, speech, and body posture, and are mainly based on the analysis of VIDEO, AUDIO and PICTURES.

In facial expression and body posture, properties are extracted from VIDEO and PICTURES. There are several properties identified in this section: clusters **<CLUSTERS>** (e.g. to analyze VIDEO, Lee et al. did CLUSTERING to recognize parts of the face to then calculate the geometric DISPLACEMENT of some areas (S. H. Lee et al., 2016.)); eye iris **<IRIS>** and eye edges **<EYECORNERS>** (e.g. Soleymani et al. used IRIS and EYECORNERS as reference points (Soleymani et al., 2013)); puckering of the lips **<LIPSPUCKER>;** wiping of the lips **<LIPWIPE>;** opening and lengthening of the mouth **<MOUTHOPENING>** **<MOUTHSTRETCH**>; mouth ends **<MOUTHCORNERS>;** biting of the lips **<LIPBITE**>; raising or lowering of the eyebrows **<BROWSRAISING**>; crossing of arms **<CROSSEDARMS**>; straight back **<ERECTBACK**>; sitting posture **<SITTINGPOSTURE**>; wrinkled nose **<WRINKLEDNOSE**>; wrinkled forehead **<WRINKLEDFH**>; wrinkled eyelid **<WRINKLEDEL**>; wrinkled eyes **<WRINKLEDEYES**>; and finger tapping **<FINGERTAPPING**>.

More specifically on facial expression, authors use appearance-based strategies by analyzing textures, cracks, and reliefs (Turan et al., 2015). Researchers such as Turan et al, (Turan et al., 2015), Shan et al. (Shan, Gong, & McOwan, 2009), Yang et al. (S. Yang & Bhanu, 2011), Dhall et al. (Dhall et al., 2011) and Liu et al. (S. Liu, Zhang, & Liu, 2014), used descriptors because they are more suitable for race recognition, less sensitive to light intensity, and less dependent on the pose of the people in the images and videos. Among the descriptors present in the literature, they include: local binary pattern **<LBP**>; local phase quantization **<LPQ**>; weber local descriptor **<WLD**>; pyramid of histogram of oriented gradients **<PHOG>;** and the gabor wavelets **<GABOR**>. The LBP is the descriptor related to texture based on intensity. The LPQ is also texture descriptor but based on blur analysis. The WLD descriptor relates the image stimulus to the intensity of the original stimulus (Weber's law). PHOG is the descriptor used for object recognition. Finally, GABOR filters facilitate the representation of facial properties (Shen, Bai, & Fairhurst, 2007). These descriptors are widely used and can represent facial expressions at various levels: intensity; phase; and shape (Turan et al., 2015).

In speaking, several properties were found: the Mel Frequency Cepstral Coefficients **<MFCC>** are ideal for processing properties related to emotional recognition problems (Sato, N.; Obuchi, 2007) (Korkmaz & Atasoy, 2015) (they are widely used in automatic speech recognition systems for oral speech and speakers (Cryptography, 2009) because they mimic the functioning of the human ear (Korkmaz & Atasoy, 2015)); the Teager Energy **<TEAE**>; Discrete Wavelet Transform coefficients **<DWTC**>; Linear Predictive Cepstral Coefficients **<LPCC>;** Mel Energy Spectral Dynamic Coefficients **<MEDC**>; shimmer **<SHIM>** (frequency of change from peak to peak variability of amplitude); Spectral Roll Off **<SPRO**>; spectral flux **<SPFL**>; Spectral Centroid **<SPCE**>; and Harmonic to Noise Ratio **<HNR**>; and the zero Crossing Rate **<ZCR>** represents the speed of signal change (e.g. positive / negative) in a given time period (Lalitha et al., 2015).

Other less commonly used properties were also identified: Chen et al. calculated the contour **<CONTOUR>** of PITCH (L. S. Chen et al., 1998); Singh et al. used an estimate for people's body posture (stick pose) <SINGH> (Singh et al., 2015).

RESEARCH	EXTRACTED PROPERTIES	
	EXP. FACIAL, ORAL AND BODY POSTURE	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)	(HEAD) <ANGLE>.	**(PHYSIOLOGICAL CONTEXT)** (EMG) <WL, WAMP, AR, MAV, MAVS>, [EMG] <<EMGCOR, EMGZYG> <MAX, MIN>> and (EOG) <SACCADE <THRESHOLD, MAX>>.
S. H. Lee et al. (S. H. Lee et al., 2016)	[FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)] <LBP, LPQ, GABOR, DISTANCE, SHAPE, CLUSTERS <CENTROID>, DISPLACEMENT>.	**(OTHER)** {HAC}.
Eckert et al. (Eckert et al., 2016)	[FACS, CAAU] <THRESHOLD, SHAPE <AREA, DISTANCE>>.	
Gogia et al. (Gogia et al., 2016)	(HEAD) <ANGLE <TIMING>>.	**(PHYSIOLOGICAL CONTEXT)** [EEG] <THRESHOLD, MEDITATION, ATTENTION>.
Z. Zhang et al. (Z. Zhang et al., 2016)	(HEAD) <GABOR>, [HEAD] <POSITION, ANGLE <STD>> and [FACS] <SHAPE>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT**) [EMOTIONS] <CATEGORICAL>.
Adams & Robinson (Adams & Robinson, 2015)	(HEAD) <ANGLE> and [FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)] <INTENSITY>.	**(PHYSIOLOGICAL CONTEXT)** (GAZE) <DIRECTION>.
Turan et al. (Turan et al., 2015)	(FACE) <LBP, LPQ, WLD, PHOG> and (EYES) <DISTANCE>.	
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	(VOLUME) <MEAN, MEDIAN, SKEWNESS, KURTOSIS, MAX, MIN, AMP> and [SPEECH [INTERVALSPLIT, DY/DX, D Y/DX[22]]] <MFCC <MEAN, MEDIAN, SKEWNESS, KURTOSIS, MAX, MIN, AMP, ZCR>>.	
Lalitha et al. (Lalitha et al., 2015)	(SPEECH) <TEAE, DWTC, LPCC, MEDC, SHIM, SPRO, SPFL, SPCE, HNR, ZCR>.	
Singh et al. (Singh et al., 2015)	[SHOULDERS, HANDS] <SINGH, SLOPE, ANGLE>.	
Saha et al. (Saha et al., 2014)	[HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN] <POSITION, ANGLE, DISTANCE>.	**(OTHER)** (ACC) <MAX, SPEED <SUBTRACT <DISPLACEMENT>>.
Agrawal et al. (Agrawal et al., 2013)	[EYES, LIPS] <CENTROID <AREA>, CORRELATION <THRESHOLD>>.	
Soleymani et al. (Soleymani et al., 2013)	[HEAD] <POSITION>, [EYES] <IRIS <MEAN>, [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <DISTANCE>, [EYES, EYEBROWS, LIPS] <EYECORNERS <MEAN,	**(PHYSIOLOGICAL CONTEXT)** (EEG) <PSD <THETA, ALPHA, BETA, GAMMA>, SUBTRACT <PSD <HEMISPHERE <LEFT, RIGHT>>>> and (EEG) and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <CORRELATION, MEAN, STD>.

	ANGLE>> and [LIPS, MOUTH] <DISTANCE>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Vermun et al. (Vermun et al., 2013)	[HEAD] <MOTION, ANGLE>, [LIPS] <LIPSPUCKER>, [MOUTH] <MOUTHOPENING>, (EYEBROWS) <BROWSRAISING>, [ARMS] <CROSSEDARMS>, [HIP, SHOULDERS, KNEES] <ERECTBACK, SITTINGPOSTURE <LEFT, RIGHT, CENTER> and [HIP, KNEES] <CENTER <ANGLE>.	
Yang & Bhanu (S. Yang & Bhanu, 2011)	[HEAD, FACE] <LBP, LPQ>.	
Dhall et al. (Dhall et al., 2011)	[FACE] <LPQ, PHOG>.	
H. Wang et al. (H. Wang et al., 2010)	[EYES] <STATUS, THRESHOLD, LBP, PERIODS <RATIO <STATUS, DURATION>>>.	
Gunes & Piccardi (Gunes & Piccardi, 2007)	[LIPS] <LIPEBITE, LIPEWIPE, STATUS, LIPSPUCKER>, [MOUTH] <MOUTHSTRETCH, STATUS, MOUTHCORNERS>, [EYES] <MOTION, SPEED, WRINKLEDEYES>, [EYEBROWS] <BROWSRAISING, SHAPE>, [EYELIDS] <POSITION, WRINKLEDEL>, [CHEEKS, JAW] <POSITION>, [NOSE] <WRINKLEDNOSE>, [FOREHEAD] <WRINKLEDLEDFH>, [HANDS, PALMS] <POSITION>, [FINGERS] <MOTION, FINGERTAPPING, POSITION>, [HANDS, FISTS] <STATUS>, [SHOULDERS] <MOTION> and [SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK] <CONTROID, AREA, RATIO <DILATION>.	
Castellano et al. (Castellano et al., 2007)	(ARMS) <MOTION <QUANTITY, MAX, MIN>, SPEED, DISPLACEMENT, SLOPE, AMP, ACC, MAINPEAK <SLOPE, MAX, MIN>, MAX, MEAN, RATIO <MEAN, MAX>, RATIO <MAX, MAINPEAK <DURATION>, RATIO <MAINPEAK <DURATION>, DURATION>, POWER <CENTROID>, DISTANCE <MAX, CENTROID>, MAX <POSITION>.	
Sebe et al. (Sebe et al., 2006)	[HEAD] <MOTION <DIRECTION, INTENSITY>>, [SPEECH] <SPEED> and [PITCH] <MAX>.	
Busso et al. (Busso et al., 2004)	(PITCH, VOLUME) <MEAN, STD, MAX, MIN, MEDIAN> and	

	[FOREHEAD, EYEBROWS, EYES, CHEEKS] <CLUSTERS, AREA>.	
Nwe et al. (Nwe et al., 2001)	[SPEECH] <MFCC <POWER>>.	
L. S. Chen et al. (L. S. Chen et al., 1998)	[PITCH] <CONTOUR <MAX, MIN, MEAN, STD, THRESHOLD>>, (SPEECH) <RMS <POWER>> and (PITCH) <CONTOUR> [DY/DX] <MAX, MIN>.	

() represents a raw signal; {} an instrument; [] a preprocessed signal; and <> an extracted property.

5.2. PHYSIOLOGICAL ENVIRONMENT

This section presents the context-specific properties related to the physiological context variables.

There are several extracted properties related to brain activity (i.e. EEG): alpha **<ALPHA**>, beta **<BETA**>, theta **<THETA**>, delta **<DELTA>** and gamma **<GAMMA>** waves (e.g. Matlovic et al. used (EEG) [DWT] to extract ALPHA and BETA (Matlovic et al., 2016), Sano & Eng. calculated PSD in the frequency domain to extract ALPHA, BETA, THETA and DELTA (Sano & Eng, 2016), and Soleymani et al. used the PSD of THETA, ALPHA, BETA and GAMMA as properties (Soleymani et al., 2013.)); level of meditation **<MEDITATION>** and attention **<ATTENTION>** (Gogia et al. measured MEDITATION and ATTENTION in learning environments from the (EEG) (Gogia et al., 2016)); and Matiko et al. used the activity of the left and right **<HEMISPHERE>** hemispheres (Matiko et al., 2014).

Also on cardiac activity the authors extract properties: the pNNx **<PNNX>** is a metric used in HRV signal analysis and represents the average number of times per unit time at which the change in normal sinus N-N intervals exceeds x milliseconds (e.g. PNN50 represents the percentage of intervals that successively differ by more than 50 milliseconds (Zenonos et al., 2016)) (Mietus, Peng, Henry, Goldsmith, & AL, 2015) (Electrophysiology, 1996b); the Heart Rate Variability Index **<HRVI>** which represents the division of the IBI by the height of the histogram of all IBIs (Zenonos et al., 2016); the Heart Rate Variability Triangular Index **<HRVTI>** is also a HRV metric that represents the integral of the density of the N-N intervals divided by the maximum of the density distribution (Electrophysiology, 1996b) suitable for use in longitudinal studies (Mehta et al., 2002); the Triangular Interpolation of N-N Interval Histogram **<TINN>** is the base size of the distribution measured as the base of a triangle approximating the N-N interval distribution (Jarkovska et al., 2016) (Electrophysiology, 1996b); and the Standard Deviation of N-N Intervals **<SDNNI>** (analysis of SDNN in intervals) (Bonnemeier et al., 2003).

Muscle activity is essentially measured by placing sensors on the corrugator supercilli muscle group **<EMGCOR**>, zygomaticus major muscle **<EMGZYG>** and levator labii superioris **<LEVATOR>** (e.g. Basu et al. used EMGCOR and EMGZYG in their research (Basu et al., 2016), and Vrana who used EMGCOR, EMGZYG, and LEVATOR (Scott R. Vrana, 1993.)). Some authors characterize muscle activity through properties that represent the functional activity of muscles (e.g. Mandryk et al. (Mandryk & Atkins, 2007) extracted smiling and frowning from the EMG **<SMILING> <FROWNING>** representing the activity of the zygomaticus major and corrugator supercilli muscles respectively (Partala et al., 2005.)). The following extracted properties were also identified: muscle contractions **<CONTRACTIONS>** (e.g. used by Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)); muscle tension **<TENSION> (**e.g. used by Vrana (Scott R.

Vrana, 1993)); and muscle activity **<MUSCLE> (**e.g. used Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)).

To researchers also use extracted properties related to eye activity: sudden eye movements simultaneously fixing two or more points **<SACCADE>** (Aracena et al., 2016) (e.g. used by Perdiz et al. (Perdiz et al., 2017.)); dilation **<DILATION>** of the PUPIL (e.g. used by Aracena et al. (Aracena et al., 2016)); gaze fixation **<FIXATION>** (e.g. used by Babiker et al. (Babiker et al., 2013)); and horizontal eye movement **<EOGH>** and vertical eye movement **<EOGV>** (e.g. Cruz et al. detected eye movements by applying LDA to data collected from the EOG with the goal of classifying the type of movement (Cruz et al., 2015). One of the most used properties at the eye activity level is the size of the PUPIL. Some authors refer to the size of the PUPIL as DIAMETER, others as SIZE, and still others as DILATION. DILATION can refer to the amount of increase or decrease of the PUPIL. However, DIAMETER and SIZE are both values that indicate the size of the PUPIL. For this reason, we decided to unify them into the single token DIAMETER.

RESEARCH	EXTRACTED PROPERTIES	
	PHYSIOLOGICAL ENVIRONMENT	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)	(EMG) <WL, WAMP, AR, MAV, MAVS>, [EMG] <<EMGCOR, EMGZYG> <MAX, MIN>> and (EOG) <SACCADE <THRESHOLD, MAX>>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE)** (HEAD) <ANGLE>.
Matlovic et al. (Matlovic et al., 2016)	(EEG) <<ALPHA, BETA> <STRENGTH, SUBTRACT, POWER, MEAN, RATIO>>.	
Gogia et al. (Gogia et al., 2016)	[EEG] <THRESHOLD, MEDITATION, ATTENTION>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE**) (HEAD) <ANGLE <TIMING>>.
Sano & Eng (Sano & Eng, 2016)	(EEG) <PSD <PERIODS <<ALPHA, BETA, THETA, DELTA>>, AMP <MEAN, STD, MEDIAN>>, [EDA] <THRESHOLD, PKF <MEAN, STD, MEDIAN>> and [EDA] and (ST) <PERIODS <ADL <AMP <MEAN, MEDIAN, STD>>>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (AGE, PERSON, ACADGR) <MEAN, MEDIAN, STD>, (STRESS, HEALTH, ANEXIETY, ACADDG, ACADCL, ACADGR, MOOD, HAPPY, ALERT, ENERGY, CALM, PERSON) <<MOTORICAL <MEAN, MEDIAN, STD>, (PHYSI <CATEGORICAL <DURATION>, (SLEEP>, (SLEEP)CATEGORICAL <MEAN, MEDIAN, STD>>, (PHYSI) <CATEGORICAL <DURATION>>, (SLEEP) and [ACC] <<MOTION <LEVEL>> <SLEEPKIND>>, [SLEEP] <<WAKEUPKIND, DURATION, COUNT, TIMING, REGULARITY, LATENCY, AWAKENINGS> <MEAN, MEDIAN, STD>>, (NAP) <DURATION, COUNT>, (EMAIL) <<OUTGOING, INCOMING, INTERLOCUTORS> <PERIODS <COUNT, MEAN, STD> <DURATION, TIMING <MEAN, MEDIAN, STD>, INTERLOCUTORS <OUTGOING, INCOMING> <COUNT>, (SMS) <TIMING <MEAN, MEDIAN, STD>, COUNT, INTERLOCUTORS, INCOMING, PERIODS <OUTGOING <COUNT> <COUNT>, (SOCIAL, FTF) <<AFFINITY, <INTERACTIONS <QUALITY> <COUNT, TIMING, REGULARITY>>, (SCREEN) <COUNT, TIMING, PERIODS <DURATION>, (LOCAL) <PERIODS <DISTANCE <MEDIAN, STD><>, (CAFFEI) <LASTTIME>, (ACADST, ACADEX) <DURATION> and (ACADCL) <<CLASSROOM, ONLINECLASS, SEMINAR, LAB, GROUPWORK> <DURATION>. **(OTHER)** [ACC] <MEAN, STD, MEDIAN, MAG <THRESHOLD>, MOTION <LEVEL>, <MEAN, STD>>, [ACC [ADL]] <PERIODS <COUNT, MEAN, MEDIAN, STD>> and (LIGHT) <PERIODS <MEAN, STD>>.

Zhao et al. (Zhao et al., 2016)	[IBI] <SDNNI, PNNX, HRVTI, TINN, HR <MEAN, STD>, PSD <LF/HF>, POINCARE <STD>, ENTROPY, DFA> and [RESP] <PKF, MEAN, MEDIAN, PSD <PLF, PHF>, POINCARE <STD>, DFA>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** [EMOTIONS] <CATEGORICAL>.
Zenonos et al. (Zenonos et al., 2016)	[IBI] <MEAN, STD, PNNX, HRVI, TINN, POINCARE <STD>>, [IBI [BANDS]] <PSD <LF/HF>> and (HR) <ENTROPY, DFA>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (MOOD, EMOTIONS) <CATEGORICAL>.
Basu et al. (Basu et al., 2016)	(EMG) <EMGCOR, EMGZYG>, (ECG, HR, PR, RESP(RR), EDA, ST, EMG <EMGCOR, EMGZYG>) <MEAN, STD, MAV1D, MAV2D> and [ECG, HR, PR, RESP(RR), EDA, ST, EMG <EMGCOR, EMGZYG>] <MAV1D, MAV2D>.	
Aracena et al. (Aracena et al., 2016)	(PUPIL) <DIAMETER>, [PUPIL] <DILATION <DIAMETER>, SIZE <MEAN>, and [GAZE] <DIRECTION>.	
Adams & Robinson (Adams & Robinson, 2015)	(GAZE) <DIRECTION>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE**) (HEAD) <ANGLE> and [FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)] <INTENSITY>.
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)	[((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA] <MEAN, MEDIAN, STD>.	
Jaques et al. (Jaques et al., 2015)	(EDA) [RAW, FINALRAW, DY/DX] <PERIODS <MEAN, MAX, MIN>>, [EDA [DY/DX]] <THRESHOLD, AMP, DURATION, SHAPE, PERIODS <COUNT>, INTEGRAL, RISETIME> and [ST] <PERIODS>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (SOCIAL, CAFFEI, ALCOH, DRUGS) <CATEGORICAL>, (CALL, SMS, SCREEN) <STD>, (CALL, SMS, SCREEN) <PERIODS <MEAN, MEDIAN>, (CALL, SMS, SCREEN, ACADCL, PHYSI, ACADEX) <COUNT>, (CALL, SCREEN, ACADCL, PHYSI, ACADEX, ACADST) <DURATION>, (SLEEP, NAP) <PERIODS <DURATION>, (CALL, SMS) <TIMING, <INCOMING, OUTGOING, INTERLOCUTORS> <COUNT>, (LOCAL) <<LATITUDE, LONGITUDE> <MEDIAN> and [LOCAL [PATHSTAKEN]] <DISTANCE>. **(OTHER)** (ACC) <MAG> and [ACC] <PERIODS>.
Cruz et al. (Cruz et al., 2015)	[EOG] <<EOGH, EOGV> <THRESHOLD, MAX, MIN, MEAN, AMP>>.	
Matiko et al. (Matiko et al., 2014)	(EEG) <HEMISPHERE <LEFT, RIGHT>, ALPHA <MEAN, STD, MAV1D, MAV2D, POWER>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>. **(OTHER)** (EEG) <MATIKO>.
Soleymani et al. (Soleymani et al., 2013)	(EEG) <PSD <THETA, ALPHA, BETA, GAMMA>, SUBTRACT <PSD <HEMISPHERE <LEFT, RIGHT>>>> and (EEG) and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <CORRELATION, MEAN, STD>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE)** [HEAD] <POSITION>, [EYES] <IRIS <MEAN>, [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <DISTANCE>, [EYES, EYEBROWS, LIPS] <EYECORNERS <MEAN, ANGLE>> and [LIPS, MOUTH] <DISTANCE>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Kusserow et al. (Kusserow et al., 2013)	[HR] <MAX>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (MOOD, STRESS) <CATEGORICAL>. **(OTHER)** (ACC) <MOTION>.
Alzoubi et al.	(EMG) <EMGCOR, EMGZYG>, (ECG(HRV), RESP, EDA, EMG	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.

(Alzoubi et al., 2013)	<EMGCOR, EMGZYG>) <MEAN, MEDIAN, STD, MAX, MIN, AMP>, (EDA) <RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MIN>, RATIO <1DIFF, MAX>, (EMG <EMGZYG>) <RATIO <1DIFF, MAX>, RATIO <1DIFF, MIN>, SUBTRACT <2DIFF, MEAN>, RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, and (RESP) <SUBTRACT <2DIFF, MIN>, SUBTRACT <AMP, 2DIFF, MAX>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MAX>.	**(OTHER)** {AUBT}.
Nawasalkar et al. (Nawasalkar et al., 2013)	[NIBP] <MEAN>.	
Sano & Picard (Sano & Picard, 2013b)	[EDA] <SLOPE <THRESHOLD <COUNT>>> and [EDA] <PERIODS <AMP <MEAN, STD, MEDIAN>>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (SCREEN) <PERIODS <COUNT, STD>>, (LOCAL) <<DISTANCE, RADIUS> <MEDIAN, STD>>, (SLEEP) <<DURATION, TIMING, QUALITY> <MEAN, STD, MEDIAN>>, (SLEEP) <SLEEPCONDITIONERS>, (ELECTR) <<USAGE <LASTTIME> <MEAN, STD, MEDIAN>>, (HEALTH, MOOD, ALERT, TIRED, STRESS) <<LEVEL <PERIODS, TIMING>> <MEAN, STD, MEDIAN>>, (NAP) <TIMING, DURATION>, (CAFFEI) <<COUNT> <MEAN, STD, MEDIAN>>, (ALCOH) <<LASTTIME, COUNT, TIMING> <MEAN, STD, MEDIAN>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <PERIODS <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INCOMING, OUTGOING> <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>, (CALL) <<MISSEDCALL <MEAN, STD, MEDIAN>>, RATIO <MISSEDCALL <OUTOING, INCOMING>>, (SMS) <PERIODS <<TIMING, SIZE, COUNT, RATIO> <MEAN, STD MEDIAN>>>, (SMS) <<SIZE <INCOMING, OUTGOING>> <MEAN, STD, MEDIAN>> and (SMS) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>. **(OTHER)** (ACC) <PERIODS <MEDIAN, STD>> and (ACC) <PERIODS <MOTION <LEVEL <MEAN>>>>.
Raudonis (Raudonis, 2013)	[PUPIL] <DIAMETER <MIN, MAX>, LOCATION <THRESHOLD> and (EYES) <MOTION <SPEED>>.	
Kawai et al. (Kawai et al., 2013)	[PUPIL] <DIAMETER, AREA, MOTION, LOCATION>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Babiker et al. (Babiker et al., 2013)	[PUPIL] <DIAMETER <DILATION, MEAN, STD>>, (EYES) <MOTION> and (GAZE) <SACCADES, FIXATION>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Murad & Malkawi (Murad & Malkawi, 2012)	(EEG) <ALPHA, BETA THETA, DELTA>.	
C. Y. Chang et al. (Chang et al., 2012)	[BVP] and [ECG, BVP, PR] <MAX>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)	[ECG(HRV)] <PSD, MEAN, MIN, MAX, VAR, STD, SKEWNESS>, (PPG) <MEAN, VAR, STD, SKEWNESS, KURTOSIS> and [PUPIL] <DILATION,	

	DIAMETER <MEAN, MAX, KURTOSIS>.	
Hernandez et al. (Hernandez et al., 2011)	[EDA] [PEAKDETECT] <MEAN> and [EDA] <MEAN, DURATION, MAX, MIN, STD, SLOPE, ZEROCROSSINGS <COUNT>, QUANTILE <THRESHOLD>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (STRESS) <CATEGORICAL>, (CALL) [LABELING] <COUNT, MEAN, DURATION, MAX, MIN, STD, SLOPE, ZEROCROSSINGS <COUNT>, QUANTILE <THRESHOLD>.
Bos (Bos, 2010)	[EEG] <ALPHA, BETA, RATIO <BETA, ALPHA>, POWER <ALPHA>, POWER <BETA>, POWER <ALPHA, BETA>, RATIO <BETA, POWER <ALPHA>, RATIO <POWER <BETA>, POWER <ALPHA>.	
Y. Liu et al. (Y. Liu et al., 2010)	(EEG) <ALPHA, THETA, BETA, DELTA, GAMMA> and (EEG) [FD] <MEAN, HEMISPHERE <LEFT, RIGHT>, THRESHOLD>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL, LEVEL>.
Setz et al. (Setz et al., 2010)	(EDA) [PEAKDETECT] <RATIO <COUNT, DURATION>, HEIGHT <MEAN>, TIMING, QUANTILE <THRESHOLD>> and [EDA] <PHASES <LEVEL <MEAN, MAX, MIN, SLOPE>>>.	
J. Kim & Andre (J. Kim & André, 2008)	(ECG(HR, HRV)) [FOURIER [BANDS]] <POWER <MEAN, LF/HF>, MAG <MAX>, (ECG) [PEAKDETECT] <ENTROPY>, [ECG(HRV)] <N-N <MEAN, STD, COUNT>, 1DIFF <STD>, RATIO, R-R <POINCARE, STD>, ENTROPY>, [ECG(HRV)] [BANDS] <PSD <POWER, DMF>, LF/HF>, (RESP (RR, BRV)) [BANDS] <POWER <MEAN>, MAG <MAX>, (RESP (RR, BRV)), (RESP (RR)) <MEAN> [LPF] <ZEROCROSSINGS <COUNT>, (RESP (BRV)) <MEAN, STD, 1DIFF <STD>, POINCARE>, (RESP (BRV)) [BANDS] <PKF, POWER, RATIO <POWER, BANDS>>, [EDA] <MEAN, STD, ZEROCROSSINGS <COUNT>, MAX>, [EDA] [DY/DX, D2Y/DX2] <MEAN>, (EMG) <MEAN> and [EMG] <STD>.	
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	(ECG(HRV)) <PNNX>, (ECG(HR, HRV, IBI)) <LF/HF>, (RESP(RR)) <AMP>, (RESP(RDEP)) <COUNT, THRESHOLD>, [EDA] <MEDIAN, AMP, DURATION>, (EDA) [LPF] <TPOINTS <COUNT>, CHANGES>, (EMG) <<EMGCOR, EMGZYG> <CONTRACTIONS <COUNT>, MUSCLE <CHANGES>, STD>> and (ST) <MEAN, CHANGES>.	(EMOTIONS) <CATEGORICAL>.
Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)	[PUPIL] <DIAMETER <CHANGES, MEAN, AMP, MAX>>, [EDA] <MAX, VAR> and (ECG(HR, IBI)) <PERIODS <MEAN>>.	
Mandryk & Atkins (Mandryk & Atkins, 2007)	[EDA] <MIN, MAX>, [EMG] <SMILING, FROWNING> and	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.

	[ECG(HR), EDA, EMG] <MEAN, STD>.	
Zhai & Barreto (Zhai & Barreto, 2006)	(PUPIL) <DIAMETER> [-NOISE [FAKEDATA]] <MEAN>, (BVP(IBI)) <PSD <LF/HF>, MEAN, STD, AMP>, [EDA] <COUNT, MEAN, AMP, RISETIME, POWER> and [ST] <SLOPE, MEAN>.	**(OTHER)** (TEMP, LIGHT) <INTENSITY>.
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	[EDA] <PERIODS <MAG <SUM>, DURATION <SUM>, INTEGRAL <SUM>, MEAN, VAR>, (EDA) [PEAKDETECT] <COUNT>, [EMG] [NORM] <MEAN, VAR>, [RESP] <VAR, MEAN>, (RESP) [BANDS] <PSD <POWER <MEAN>, (ECG(HR)) <LF/HF, MEAN>, (ECG(HRV)) <PERIODS <LF/HF, LFMF/HF>, MEAN> and [EDA, EMG, RESP, ECG(HR, HRV) and [STRESS] <COVAR, STD>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** [STRESS] <LEVEL <PERIODS <MEAN, STD>>.
Herbon et al. (Herbon et al., 2005)	(PUPIL) <DILATION> and (HR, EDA, ST, PUPIL) <STD <THRESHOLD>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL <STD>>.
Partala et al. (Partala et al., 2005)	[EMG] <<EMGZYG <SMILING>, EMGCOR <FROWNING> <MEAN>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Van Eck et al. (van Eck et al., 2005)	[CORT] <TIMING, MEAN, SLOPE, VAR, COVAR, STD>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS) <CATEGORICAL> and (STRESS) <STD, MEAN, TIMING, UNPLEASANTNESS, IMPORTANCE, PREDICTABILITY, CONTROLLABILITY, LASTSTRESS>.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	[HR, EDA, ST] <MIN, MAX, MEAN, VAR>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
K. H. Kim et al. (K. H. Kim et al., 2004)	[ECG(HRV)] <MEAN, STD, DY/DX>, (EDA) <MEAN, ZEROCROSSINGS <COUNT>, MAX, AMP, DURATION> and [EDA] <DY/DX>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Haag et al. (Haag et al., 2004)	[ECG(HR)] <MIN, MAX, MEAN, STD>, [PPG(BVP(HR))] <MIN, MAX, AMP, STD, RATIO <SUM>, [EDA] <SLOPE, MEAN, STD>, [RESP] <SLOPE, MEAN, STD, AMP <STD>, SPEED <STD>, [EMG] <SLOPE, MEAN, STD, AMP> and (ST) <SLOPE, MEAN, STD>.	
Partala & Surakka (Partala & Surakka, 2003)	[PUPIL] <DIAMETER, DILATION <MEAN>, FIXATION, VAR>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
C J Harmer et al. (C J Harmer et al., 2003)	(SEROT) <TIMING, LEVEL, VAR, MEDIAN>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (MOOD, ENERGY, EMOTIONS, ANXIETY) <CATEGORICAL>.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	(CORT) <MEAN>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	[ECG(HR, HRV), EDA, EMG] <MEAN, VAR, 1DIFF <MEAN>, SLOPE>, [EMG] <PERIODS <MEAN>, [EDA] <PERIODS <MAX, MIN>>,	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (STRESS) <CATEGORICAL>.

	[PPG(BVP(HR))] <MEAN, 1DIFF <MEAN>> and [RESP] <MEAN, VAR, PSD>.	
Vrijkotte et al. (Vrijkotte et al., 2000)	[ECG(HR, IBI(RMSSD))] <<PERIODS, TIMING, DURATION> <MEAN, STD>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (STRESS) <EFFORT, REWARD, OVERCOMMITMENT, RATIO <EFFORT, REWARD>, (PHYSI) and (ACC) <MOTION>, (CAFFEI, ALCOH, SMOKING) <COUNT>, (MOOD) <LEVEL> and (PERSON) <CATEGORICAL>.
Ritz et al. (Ritz et al., 2000)	[BP(SBP)] <CHANGES> and [HR, BP(SBP, DBP), ROS, RR, VT, EDA] <MEAN, STD>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
J. Healey & Picard (J. Healey & Picard, 1998)	[EMG] <PHASES <MUSCLE <MEAN>>, [EDA] <PHASES <MEAN, 1DIFF <SLOPE <MEAN>>>>, (PPG(BVP(HR))) <PHASES <MEAN, 1DIFF <CHANGES <MEAN>>>> and [RESP] <MEAN, VAR, PSD>.	
Rajita Sinha (Rajita Sinha, 1996)	(EOG) <QUANTILE <MOTION>, MEDIAN>, [ECG(HR), BP(SBP, DBP), EDA, EOG] <PERIODS <MEDIAN>, (ST, EMG) <PERIODS <MEDIAN>, and (BP(DBP)) <CHANGES>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Scott R. Vrana (Scott R. Vrana, 1993)	[EMG] <<EMGCOR, EMGZYG, LEVATOR> <PERIODS <TENSION>>>, [ECG(HR)] <CHANGES> and (EDA) <PERIODS <MEAN>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
R Sinha et al. (R Sinha et al., 1992)	[ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)] <CHANGES <MEAN, STD>, PERIODS <MEAN> <MEAN> and [BP(SBP, DBP)] <MEAN>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.

() represents a raw signal; {} an instrument; [] a preprocessed signal; and <> an extracted property.

5.3. SOCIAL AND PSYCHOLOGICAL CONTEXT

As mentioned earlier, the most commonly used instruments for collecting data from the social and psychological context are questionnaires. These instruments collect nominal or ordinal qualitative information through scales representing intensities (e.g. Likert), or a finite number of symbols, labels or names (e.g. {positive, negative}, {regular, irregular}, {poor, medium, very}, etc.). As several properties are possible to extract based on the answers given by the respondents (i.e. COUNT, MEAN, etc.) and the authors reviewed in this literature review do not always indicate details of the properties extracted from the questionnaires, we decided, in these cases, to group the properties possible to extract with the token **<CATEGORICAL>** given the categorical nature of the collected data. Included in this group are properties extracted from questionnaires answered at various points in the experiment (e.g. Sano and Eng used two context variables for STRESS (cf. pre and post-study) (Sano & Eng, 2016)).

In order to compose the <u>LOCAL</u> context variable: Jaques et al. applied the MEDIAN statistical property to the latitude **<LATITUDE>** and longitude **<LONGITUDE> of** the Global Position System (GPS) when integrating data with WiFi and mobile operator antennas (Jaques et al., 2015); Bauer et al. called the locations commonly used by participants regions of interest **<ROI>** and used this information in their study of STRESS (Bauer & Lukowicz, 2012);

Regarding CALL, SMS and EMAIL context variables, several context properties were identified: incoming communications **<INCOMING**>; outgoing communications **<OUTGOING**>; distinct number of interlocutors **<INTERLOCUTORS**>; amount of interactions only initiated and not completed **<INITIATEDONLY>** (e.g. CALL, SMS, or EMAIL only initiated and not completed or sent); amount of interactions performed as a response **<ANSWER>** (e.g. SMS in response to an SMS, CALL response to a MISSEDCALL, EMAIL response to another EMAIL); and missed (i.e. not answered) CALL **<MISSEDCALL**>.

For the PROXIMITY variable, researchers use the number of detected devices **<DEVICES>** (e.g. bluetooth) to determine the existence of other people nearby. For the SOCIAL context variable, the following properties are used: quality of social interactions **<INTERACTIONS**>; and affinity with interlocutors (i.e. proximity in the social network) **<AFFINITY**>. Regarding the variable ACADCL the researchers discriminate the time spent: in physical classrooms **<CLASSROOM**>; virtual classrooms **<ONLINECLASS**>; seminars **<SEMINAR**>; labs **<LAB**>; and group work **<GROUPWORK**>. Regarding the variables ACADST, ACADEX and PHYSI researchers essentially use generic properties such as DURATION (e.g. Sano & Eng calculated the DURATION of ACADST, ACADEX and PHYSI in their research (Sano & Eng, 2016)).

Properties related to the SLEEP variable include properties related to sleep and waking: manner of waking **<WAKEUPKIND>** (e.g. spontaneous waking, alarm clock, etc.); unexpected awakenings during the night **<WAWAKENINGS**>; differentiation of sleep types **<SLEEPKIND>** (e.g. night sleep, naps, etc.); and sleep conditioners (e.g. set time to go to sleep and to wake up) **<SLEEPCONDITIONERS**>.

Regarding the STRESS variable, properties are used with the aim of better categorizing STRESS: unpleasantness **<UNPLEASANTNESS**>; importance **<IMPORTANCE**>; predictability **<PREDICTABILITY**>; controllability **<CONTROLLABILITY>;** last stressful event **<LASTSTRESS**>; extrinsic effort (i.e. level of job demands (Vrijkotte et al.)) **<EFFORT**>; reward (e.g. salary, status, appreciation, etc. (Vrijkotte et al., 2000)) **<REWARD**>; and ability to excel **<OVERCOMMITMENT**>. The PERSON variable is heavily assessed through the BFIPT. This instrument measures personality traits based on five dimensions: extraversion **<EXTRAVERSION**>; neuroticism **<NEUROTICISM**>; agreeableness **<AGREEABLENESS**>; conscientiousness **<CONSCIENTIOUSNESS>;** and openness to experience **<OPENNESS**>.

RESEARCH	EXTRACTED PROPERTIES	
	SOCIAL AND PSYCHOLOGICAL CONTEXT	OTHER
Z. Zhang et al. (Z. Zhang et al., 2016)	[EMOTIONS] <CATEGORICAL>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE)** (HEAD) <GABOR>, [HEAD] <POSITION, ANGLE <STD>> and [FACS] <SHAPE>.
Sano & Eng (Sano & Eng, 2016)	(AGE, PERSON, ACADGR) <MEAN, MEDIAN, STD>, (STRESS, HEALTH, ANEXIETY, ACADDG, ACADCL, ACADGR, MOOD, HAPPY, ALERT, ENERGY, CALM, PERSON) <<MOTORICAL <MEAN, MEDIAN, STD>, (PHYSI <CATEGORICAL <DURATION>, (SLEEP>, (SLEEP)CATEGORICAL <MEAN, MEDIAN, STD>>, (PHYSI) <CATEGORICAL <DURATION>>, (SLEEP) and [ACC] <<MOTION <LEVEL>> <SLEEPKIND>>, [SLEEP]	**(PHYSIOLOGICAL CONTEXT)** (EEG) <PSD <PERIODS <<ALPHA, BETA, THETA, DELTA>>, AMP <MEAN, STD, MEDIAN>>, [EDA] <THRESHOLD, PKF <MEAN, STD, MEDIAN>> and [EDA] and (ST) <PERIODS <ADL <AMP <MEAN, MEDIAN, STD>>>>. **(OTHER)** [ACC] <MEAN, STD, MEDIAN, MAG <THRESHOLD>, MOTION <LEVEL>, <MEAN, STD>>, [ACC [ADL]] <PERIODS <COUNT, MEAN, MEDIAN, STD>> and (LIGHT) <PERIODS <MEAN, STD>>.

	<<WAKEUPKIND, DURATION, COUNT, TIMING, REGULARITY, LATENCY, AWAKENINGS> <MEAN, MEDIAN, STD>>, (NAP) <DURATION, COUNT>, (EMAIL) <<OUTGOING, INCOMING, INTERLOCUTORS> <PERIODS <COUNT, MEAN, STD> <DURATION, TIMING <MEAN, MEDIAN, STD>, INTERLOCUTORS <OUTGOING, INCOMING> <COUNT>, (SMS) <TIMING <MEAN, MEDIAN, STD>, COUNT, INTERLOCUTORS, INCOMING, PERIODS <OUTGOING <COUNT> <COUNT>, (SOCIAL, FTF) <<AFFINITY, <INTERACTIONS <QUALITY> <COUNT, TIMING, REGULARITY>>, (SCREEN) <COUNT, TIMING, PERIODS <DURATION>, (LOCAL) <PERIODS <DISTANCE <MEDIAN, STD><>, (CAFFEI) <LASTTIME>, (ACADST, ACADEX) <DURATION> and (ACADCL) <<CLASSROOM, ONLINECLASS, SEMINAR, LAB, GROUPWORK> <DURATION>.	
Zhao et al. (Zhao et al., 2016)	[EMOTIONS] <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT**) [IBI] <SDNNI, PNNX, HRVTI, TINN, HR <MEAN, STD>, PSD <LF/HF>, POINCARE <STD>, ENTROPY, DFA> and [RESP] <PKF, MEAN, MEDIAN, PSD <PLF, PHF>, POINCARE <STD>, DFA>.
Zenonos et al. (Zenonos et al., 2016)	(MOOD, EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT**) [IBI] <MEAN, STD, PNNX, HRVI, TINN, POINCARE <STD>>, [IBI [BANDS]] <PSD <LF/HF>> and (HR) <ENTROPY, DFA>.
Jaques et al. (Jaques et al., 2015)	(SOCIAL, CAFFEI, ALCOH, DRUGS) <CATEGORICAL>, (CALL, SMS, SCREEN) <STD>, (CALL, SMS, SCREEN) <PERIODS <MEAN, MEDIAN>, (CALL, SMS, SCREEN, ACADCL, PHYSI, ACADEX) <COUNT>, (CALL, SCREEN, ACADCL, PHYSI, ACADEX, ACADST) <DURATION>, (SLEEP, NAP) <PERIODS <DURATION>, (CALL, SMS) <TIMING, <INCOMING, OUTGOING, INTERLOCUTORS> <COUNT>, (LOCAL) <<LATITUDE, LONGITUDE> <MEDIAN> and [LOCAL [PATHSTAKEN]] <DISTANCE>.	**(PHYSIOLOGICAL CONTEXT)** (EDA) [RAW, FINALRAW, DY/DX] <PERIODS <MEAN, MAX, MIN>>, [EDA [DY/DX]] <THRESHOLD, AMP, DURATION, SHAPE, PERIODS <COUNT>, INTEGRAL, RISETIME> and [ST] <PERIODS>. **(OTHER)** (ACC) <MAG> and [ACC] <PERIODS>.
Matiko et al. (Matiko et al., 2014)	EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** (EEG) <HEMISPHERE <LEFT, RIGHT>, ALPHA <MEAN, STD, MAV1D, MAV2D, POWER>>. **(OTHER)** (EEG) <MATIKO>.
Bogomolov et al. (Bogomolov et al., 2014)	(STRESS) <CATEGORICAL <SKEWNESS, KURTOSIS>>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <<INCOMING, OUTGOING, MISSEDCALL> <COUNT>>, (CALL)	**(OTHER)** (WEATHER) <PERIODS <TEMP <MEAN>, PRESSURE, PRECIPITATION, HUMIDITY, VISIBILITY, WIND <SPEED><SPEED>.

	<INTERLOCUTORS <OUTGOING, INCOMING, MISSEDCALL> <COUNT, ENTROPY>>, (CALL) <RATIO <INTERLOCUTORS <CALL, SMS, PROXIMITY>>, (SMS) <INCOMING, OUTGOING <COUNT>>, (SMS) <INTERLOCUTORS <INCOMING, OUTGOING> <COUNT, ENTROPY>>, (SMS) <RATIO <INTERLOCUTORS <CALL, SMS, PROXIMITY>>>, (CALL) <PERIODS <INCOMING, OUTGOING>>, (CALL, SMS) <INITIATEDONLY <PERIODS <<COUNT>>, ELAPSEDTIME <MEAN, VAR>>, [SMS] <ANSWER <RATIO, LATENCY>>, (CALL, SMS) <PERIODS <MEAN, MEDIAN, MIN, MAX, QUANTILE, STD, VAR>> and (PROXIMITY) <DEVICES <ELAPSEDTIME <MEAN, VAR>, ENTROPY>, PERIODS <USUAL <COUNT> <COUNT>.	
Soleymani et al. (Soleymani et al., 2013)	(EMOTIONS) <CATEGORICAL>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE)** [HEAD] <POSITION>, [EYES] <IRIS <MEAN>, [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <DISTANCE>, [EYES, EYEBROWS, LIPS] <EYECORNERS <MEAN, ANGLE>> and [LIPS, MOUTH] <DISTANCE>. **(PHYSIOLOGICAL CONTEXT)** (EEG) <PSD <THETA, ALPHA, BETA, GAMMA>, SUBTRACT <PSD <HEMISPHERE <LEFT, RIGHT>>>> and (EEG) and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <CORRELATION, MEAN, STD>.
Kusserow et al. (Kusserow et al., 2013)	(MOOD, STRESS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [HR] <MAX>. **(OTHER)** (ACC) <MOTION>.
Alzoubi et al. (Alzoubi et al., 2013)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** (EMG) <EMGCOR, EMGZYG>, (ECG(HRV), RESP, EDA, EMG <EMGCOR, EMGZYG>) <MEAN, MEDIAN, STD, MAX, MIN, AMP>, (EDA) <RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MIN>, RATIO <1DIFF, MAX>, (EMG <EMGZYG>) <RATIO <1DIFF, MAX>, RATIO <1DIFF, MIN>, SUBTRACT <2DIFF, MEAN>, RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, and (RESP) <SUBTRACT <2DIFF, MIN>, SUBTRACT <AMP, 2DIFF, MAX>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MAX>. **(OTHER)** {AUBT}.
Sano & Picard (Sano & Picard, 2013b)	(SCREEN) <PERIODS <COUNT, STD>>, (LOCAL) <<DISTANCE, RADIUS> <MEDIAN, STD>>, (SLEEP) <<DURATION, TIMING, QUALITY> <MEAN, STD, MEDIAN>>, (SLEEP) <SLEEPCONDITIONERS>, (ELECTR) <<USAGE <LASTTIME> <MEAN, STD, MEDIAN>>, (HEALTH, MOOD, ALERT, TIRED, STRESS) <<LEVEL <PERIODS, TIMING>> <MEAN, STD, MEDIAN>>, (NAP) <TIMING, DURATION>, (CAFFEI) <<COUNT> <MEAN, STD, MEDIAN>>, (ALCOH)	**(PHYSIOLOGICAL CONTEXT)** [EDA] <SLOPE <THRESHOLD <COUNT>>> and [EDA] <PERIODS <AMP <MEAN, STD, MEDIAN>>>. **(OTHER)** (ACC) <PERIODS <MEDIAN, STD>> and (ACC) <PERIODS <MOTION <LEVEL <MEAN>>>>.

	<<LASTTIME, COUNT, TIMING> <MEAN, STD, MEDIAN>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <PERIODS <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INCOMING, OUTGOING> <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>, (CALL) <<MISSEDCALL <MEAN, STD, MEDIAN>>, RATIO <MISSEDCALL <OUTOING, INCOMING>>, (SMS) <PERIODS <<TIMING, SIZE, COUNT, RATIO> <MEAN, STD MEDIAN>>>, (SMS) <<SIZE <INCOMING, OUTGOING>> <MEAN, STD, MEDIAN>> and (SMS) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>.	
Kawai et al. (Kawai et al., 2013)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [PUPIL] <DIAMETER, AREA, MOTION, LOCATION>.
Babiker et al. (Babiker et al., 2013)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [PUPIL] <DIAMETER <DILATION, MEAN, STD>>, (EYES) <MOTION> and (GAZE) <SACCADES, FIXATION>.
LikamWa et al. (LiKamWa et al., 2013)	[MOOD] <PERIODS <COUNT, STD <MEAN, MAX>>, (EMAIL, SMS) <INTERLOCUTORS <USUAL <COUNT, SIZE>>>, (CALL) <INTERLOCUTORS <USUAL <COUNT, DURATION>>, (APPS) <COUNT, DURATION> and (BROWSER, LOCAL) <COUNT>.	
C. Y. Chang et al. (Chang et al., 2012)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [BVP] and [ECG, BVP, PR] <MAX>.
Bauer & Lukowicz (Bauer & Lukowicz, 2012)	(LOCAL) [USUALPLACES] <DIAMETER <MAX>, DURATION <MEAN, THRESHOLD>>, [LOCAL] <ROI <TIMING, REGULARITY, COUNT <MEAN, AD, STD>>>, (PROXIMITY) <TIMING, DURATION <THRESHOLD, AD, MEAN, STSD>, COUNT <AD, MEAN, STD>> and (CALL, SMS) <<INCOMING, OUTGOING> <INTERLOCUTORS <COUNT <MEAN, STD>>, COUNT <AD, MEAN, STD>>>.	
Hernandez et al. (Hernandez et al., 2011)	(STRESS) <CATEGORICAL>, (CALL) [LABELING] <COUNT, MEAN, DURATION, MAX, MIN, STD, SLOPE, ZEROCROSSINGS <COUNT>, QUANTILE <THRESHOLD>>.	**(PHYSIOLOGICAL CONTEXT)** [EDA] [PEAKDETECT] <MEAN> and [EDA] <MEAN, DURATION, MAX, MIN, STD, SLOPE, ZEROCROSSINGS <COUNT>, QUANTILE <THRESHOLD>>.
N. Lane et al. (N. Lane et al., 2011)	(DEPRESSION, SLEEP, WELLBEING) <CATEGORICAL> and [SLEEP, PHYSI, TALK] <DURATION, MEAN, VAR>.	**(OTHER)** (ACC) <MEAN, VARIANCE, PERIODS <MOTION <COUNT, DURATION>>.
Y. Liu et al. (Y. Liu et al., 2010)	(EMOTIONS) <CATEGORICAL, LEVEL>.	**(PHYSIOLOGICAL CONTEXT)**

		(EEG) <ALPHA, THETA, BETA, DELTA, GAMMA> and (EEG) [FD] <MEAN, HEMISPHERE <LEFT, RIGHT>, THRESHOLD>.
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** (ECG(HRV)) <PNNX>, (ECG(HR, HRV, IBI)) <LF/HF>, (RESP(RR)) <AMP>, (RESP(RDEP)) <COUNT, THRESHOLD>, [EDA] <MEDIAN, AMP, DURATION>, (EDA) [LPF] <TPOINTS <COUNT>, CHANGES>, (EMG) <<EMGCOR, EMGZYG> <CONTRACTIONS <COUNT>, MUSCLE <CHANGES>, STD>> and (ST) <MEAN, CHANGES>.
Mandryk & Atkins (Mandryk & Atkins, 2007)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [EDA] <MIN, MAX>, [EMG] <SMILING, FROWNING> and [ECG(HR), EDA, EMG] <MEAN, STD>.
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)	[STRESS] <LEVEL <PERIODS <MEAN, STD>>.	**(PHYSIOLOGICAL CONTEXT)** [EDA] <PERIODS <MAG <SUM>, DURATION <SUM>, INTEGRAL <SUM>, MEAN, VAR>, (EDA) [PEAKDETECT] <COUNT>, [EMG] [NORM] <MEAN, VAR>, [RESP] <VAR, MEAN>, (RESP) [BANDS] <PSD <POWER <MEAN><>, (ECG(HR)) <LF/HF, MEAN>, (ECG(HRV)) <PERIODS <LF/HF, LFMF/HF>, MEAN> and [EDA, EMG, RESP, ECG(HR, HRV) and [STRESS] <COVAR, STD>.
Herbon et al. (Herbon et al., 2005)	(EMOTIONS) <CATEGORICAL <STD>>.	**(PHYSIOLOGICAL CONTEXT)** (PUPIL) <DILATION> and (HR, EDA, ST, PUPIL) <STD <THRESHOLD>.
Partala et al. (Partala et al., 2005)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [EMG] <<EMGZYG <SMILING>, EMGCOR <FROWNING> <MEAN>.
Van Eck et al. (van Eck et al., 2005)	(LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS) <CATEGORICAL> and (STRESS) <STD, MEAN, TIMING, UNPLEASANTNESS, IMPORTANCE, PREDICTABILITY, CONTROLLABILITY, LASTSTRESS>.	**(PHYSIOLOGICAL CONTEXT)** [CORT] <TIMING, MEAN, SLOPE, VAR, COVAR, STD>.
Lisetti & Nasoz (Lisetti & Nasoz, 2004)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [HR, EDA, ST] <MIN, MAX, MEAN, VAR>.
K. H. Kim et al. (K. H. Kim et al., 2004)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [ECG(HRV)] <MEAN, STD, DY/DX>, (EDA) <MEAN, ZEROCROSSINGS <COUNT>, MAX, AMP, DURATION> and [EDA] <DY/DX>.
Partala & Surakka (Partala & Surakka, 2003)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [PUPIL] <DIAMETER, DILATION <MEAN>, FIXATION, VAR>.
C J Harmer et al. (C J Harmer et al., 2003)	(MOOD, ENERGY, EMOTIONS, ANXIETY) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** (SEROT) <TIMING, LEVEL, VAR, MEDIAN>.
Buchanan & Lovallo (Buchanan & Lovallo, 2001)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** (CORT) <MEAN>.
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)	(STRESS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [ECG(HR, HRV), EDA, EMG] <MEAN, VAR, 1DIFF <MEAN>, SLOPE>, [EMG] <PERIODS <MEAN>, [EDA] <PERIODS <MAX, MIN>>, [PPG(BVP(HR))] <MEAN, 1DIFF <MEAN>> and [RESP] <MEAN, VAR, PSD>.
Vrijkotte et al.	(STRESS) <EFFORT, REWARD, OVERCOMMITMENT, RATIO	**(PHYSIOLOGICAL CONTEXT)**

(Vrijkotte et al., 2000)	<EFFORT, REWARD>, (PHYSI) and (ACC) <MOTION>, (CAFFEI, ALCOH, SMOKING) <COUNT>, (MOOD) <LEVEL> and (PERSON) <CATEGORICAL>.	[ECG(HR, IBI(RMSSD))] <<PERIODS, TIMING, DURATION> <MEAN, STD>>.
Ritz et al. (Ritz et al., 2000)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [BP(SBP)] <CHANGES> and [HR, BP(SBP, DBP), ROS, RR, VT, EDA] <MEAN, STD>.
Rajita Sinha (Rajita Sinha, 1996)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** (EOG) <QUANTILE <MOTION>, MEDIAN>, [ECG(HR), BP(SBP, DBP), EDA, EOG] <PERIODS <MEDIAN>>, (ST, EMG) <PERIODS <MEDIAN>> and (BP(DBP)) <CHANGES>.
Scott R. Vrana (Scott R. Vrana, 1993)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [EMG] <<EMGCOR, EMGZYG, LEVATOR> <PERIODS <TENSION>>>, [ECG(HR)] <CHANGES> and (EDA) <PERIODS <MEAN>>.
R Sinha et al. (R Sinha et al., 1992)	(EMOTIONS) <CATEGORICAL>.	**(PHYSIOLOGICAL CONTEXT)** [ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)] <CHANGES <MEAN, STD>, PERIODS <MEAN> <MEAN> and [BP(SBP, DBP)] <MEAN>.

() represents a raw signal; {} an instrument; [] a preprocessed signal; and <> an extracted property.

5.4. OTHER

This section includes other extracted properties not included in the previous sections that are related to the other context variables.

The WEATHER context variable was determined by collecting several sensors: ambient temperature (TEMP) (already presented in this document as a context variable); humidity **<HUMIDITY>;** visibility **<VISIBILITY>;** wind **<WIND**>; pressure **<PRESSURE**>; and precipitation **<PRECIPITATION**>.

Extracted properties were also identified that had already been presented as variables collected directly from the context (e.g. Castellano et al. extracted the <ACC> based on the difference between VIDEO frames using EYESWEB (Castellano et al.)).

Finally, this section also includes the authors' specific properties: Matiko et al. created an oscillatory property **<MATIKO>** that is calculated from the local maximum and local minimum of the EEG signal, and that tells how the POWER of the signal is related to the activations and inactivations of brain regions (Matiko et al., 2014).

Also in this section, some tools were identified to support the extracted properties: S. H. lee et al. used MATLAB's HAC to support the determination of CLUSTERS (S. H. Lee et al., 2016); and Alzoubi et al. used AUBT in pre-processing and extracting properties from physiological data (Alzoubi et al., 2013).

RESEARCH	EXTRACTED PROPERTIES	
	OTHER	PREVIOUS
S. H. Lee et al. (S. H. Lee et al., 2016)	{HAC}.	**(FACIAL AND ORAL EXP. AND BODY POSTURE)** [FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)] <LBP, LPQ, GABOR, DISTANCE, SHAPE, CLUSTERS <CENTROID>, DISPLACEMENT>.

Sano & Eng (Sano & Eng, 2016)	[ACC] <MEAN, STD, MEDIAN, MAG <THRESHOLD>, MOTION <LEVEL>, <MEAN, STD>>, [ACC [ADL]] <PERIODS <COUNT, MEAN, MEDIAN, STD>> and (LIGHT) <PERIODS <MEAN, STD>>.	**(PHYSIOLOGICAL CONTEXT)** (EEG) <PSD <PERIODS <<ALPHA, BETA, THETA, DELTA>>, AMP <MEAN, STD, MEDIAN>>, [EDA] <THRESHOLD, PKF <MEAN, STD, MEDIAN>> and [EDA] and (ST) <PERIODS <ADL <AMP <MEAN, MEDIAN, STD>>>>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (AGE, PERSON, ACADGR) <MEAN, MEDIAN, STD>, (STRESS, HEALTH, ANEXIETY, ACADDG, ACADCL, ACADGR, MOOD, HAPPY, ALERT, ENERGY, CALM, PERSON) <<MOTORICAL <MEAN, MEDIAN, STD>, (PHYSI <CATEGORICAL <DURATION>, (SLEEP>, (SLEEP)CATEGORICAL <MEAN, MEDIAN, STD>>, (PHYSI) <CATEGORICAL <DURATION>>, (SLEEP) and [ACC] <<MOTION <LEVEL>> <SLEEPKIND>>, [SLEEP] <<WAKEUPKIND, DURATION, COUNT, TIMING, REGULARITY, LATENCY, AWAKENINGS> <MEAN, MEDIAN, STD>>, (NAP) <DURATION, COUNT>, (EMAIL) <<OUTGOING, INCOMING, INTERLOCUTORS> <PERIODS <COUNT, MEAN, STD> <DURATION, TIMING <MEAN, MEDIAN, STD>, INTERLOCUTORS <OUTGOING, INCOMING> <COUNT>, (SMS) <TIMING <MEAN, MEDIAN, STD>, COUNT, INTERLOCUTORS, INCOMING, PERIODS <OUTGOING <COUNT> <COUNT>, (SOCIAL, FTF) <<AFFINITY, <INTERACTIONS <QUALITY> <COUNT, TIMING, REGULARITY>>, (SCREEN) <COUNT, TIMING, PERIODS <DURATION>, (LOCAL) <PERIODS <DISTANCE <MEDIAN, STD><>, (CAFFEI) <LASTTIME>, (ACADST, ACADEX) <DURATION> and (ACADCL) <<CLASSROOM, ONLINECLASS, SEMINAR, LAB, GROUPWORK> <DURATION>.
Jaques et al. (Jaques et al., 2015)	(ACC) <MAG> and [ACC] <PERIODS>.	**(PHYSIOLOGICAL CONTEXT)** (EDA) [RAW, FINALRAW, DY/DX] <PERIODS <MEAN, MAX, MIN>>, [EDA [DY/DX]] <THRESHOLD, AMP, DURATION, SHAPE, PERIODS <COUNT>, INTEGRAL, RISETIME> and [ST] <PERIODS>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (SOCIAL, CAFFEI, ALCOH, DRUGS) <CATEGORICAL>, (CALL, SMS, SCREEN) <STD>, (CALL, SMS, SCREEN) <PERIODS <MEAN, MEDIAN>, (CALL, SMS, SCREEN, ACADCL, PHYSI, ACADEX) <COUNT>, (CALL, SCREEN, ACADCL, PHYSI, ACADEX, ACADST) <DURATION>, (SLEEP, NAP) <PERIODS <DURATION>, (CALL, SMS) <TIMING, <INCOMING, OUTGOING, INTERLOCUTORS> <COUNT>, (LOCAL) <<LATITUDE, LONGITUDE> <MEDIAN> and [LOCAL [PATHSTAKEN]] <DISTANCE>.
Saha et al. (Saha et al., 2014)	(ACC) <MAX, SPEED <SUBTRACT <DISPLACEMENT>>.	**(FACIAL AND ORAL EXP. AND BODY POSTURE)** [HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN] <POSITION, ANGLE, DISTANCE>.
Matiko et al. (Matiko et al., 2014)	(EEG) <MATIKO>.	**(PHYSIOLOGICAL CONTEXT)** (EEG) <HEMISPHERE <LEFT, RIGHT>, ALPHA <MEAN, STD, MAV1D, MAV2D, POWER>>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Bogomolov et al. (Bogomolov et al., 2014)	(WEATHER) <PERIODS <TEMP <MEAN>, PRESSURE, PRECIPITATION, HUMIDITY, VISIBILITY, WIND <SPEED><SPEED>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (STRESS) <CATEGORICAL <SKEWNESS, KURTOSIS>>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <<INCOMING, OUTGOING, MISSEDCALL> <COUNT>>, (CALL) <INTERLOCUTORS <OUTGOING, INCOMING, MISSEDCALL> <COUNT, ENTROPY>>, (CALL) <RATIO <INTERLOCUTORS <CALL, SMS, PROXIMITY>>,

		(SMS) <INCOMING, OUTGOING <COUNT>>, (SMS) <INTERLOCUTORS <INCOMING, OUTGOING> <COUNT, ENTROPY>>, (SMS) <RATIO <INTERLOCUTORS <CALL, SMS, PROXIMITY>>>, (CALL) <PERIODS <INCOMING, OUTGOING>>, (CALL, SMS) <INITIATEDONLY <PERIODS <<COUNT>>, ELAPSEDTIME <MEAN, VAR>>, [SMS] <ANSWER <RATIO, LATENCY>>, (CALL, SMS) <PERIODS <MEAN, MEDIAN, MIN, MAX, QUANTILE, STD, VAR>> and (PROXIMITY) <DEVICES <ELAPSEDTIME <MEAN, VAR>, ENTROPY>, PERIODS <USUAL <COUNT> <COUNT>.
Kusserow et al. (Kusserow et al., 2013)	(ACC) <MOTION>.	**(PHYSIOLOGICAL CONTEXT)** [HR] <MAX>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (MOOD, STRESS) <CATEGORICAL>.
Alzoubi et al. (Alzoubi et al., 2013)	{AUBT}.	**(PHYSIOLOGICAL CONTEXT)** (EMG) <EMGCOR, EMGZYG>, (ECG(HRV), RESP, EDA, EMG <EMGCOR, EMGZYG>) <MEAN, MEDIAN, STD, MAX, MIN, AMP>, (EDA) <RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MIN>, RATIO <1DIFF, MAX>, (EMG <EMGZYG>) <RATIO <1DIFF, MAX>, RATIO <1DIFF, MIN>, SUBTRACT <2DIFF, MEAN>, RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, and (RESP) <SUBTRACT <2DIFF, MIN>, SUBTRACT <AMP, 2DIFF, MAX>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MAX>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (EMOTIONS) <CATEGORICAL>.
Sano & Picard (Sano & Picard, 2013b)	(ACC) <PERIODS <MEDIAN, STD>> and (ACC) <PERIODS <MOTION <LEVEL <MEAN>>>>.	**(PHYSIOLOGICAL CONTEXT)** [EDA] <SLOPE <THRESHOLD <COUNT>>> and [EDA] <PERIODS <AMP <MEAN, STD, MEDIAN>>>. **(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (SCREEN) <PERIODS <COUNT, STD>>, (LOCAL) <<DISTANCE, RADIUS> <MEDIAN, STD>>, (SLEEP) <<DURATION, TIMING, QUALITY> <MEAN, STD, MEDIAN>>, (SLEEP) <SLEEPCONDITIONERS>, (ELECTR) <<USAGE <LASTTIME> <MEAN, STD, MEDIAN>>, (HEALTH, MOOD, ALERT, TIRED, STRESS) <<LEVEL <PERIODS, TIMING>> <MEAN, STD, MEDIAN>>, (NAP) <TIMING, DURATION>, (CAFFEI) <<COUNT> <MEAN, STD, MEDIAN>>, (ALCOH) <<LASTTIME, COUNT, TIMING> <MEAN, STD, MEDIAN>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <PERIODS <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INCOMING, OUTGOING> <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>, (CALL) <<MISSEDCALL <MEAN, STD, MEDIAN>>, RATIO <MISSEDCALL <OUTOING, INCOMING>>, (SMS) <PERIODS <<TIMING, SIZE, COUNT, RATIO> <MEAN, STD MEDIAN>>>, (SMS) <<SIZE <INCOMING, OUTGOING>> <MEAN, STD, MEDIAN>> and (SMS) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>.
N. Lane et al. (N. Lane et al., 2011)	(ACC) <MEAN, VARIANCE, PERIODS <MOTION <COUNT, DURATION>>.	**(SOCIAL AND PSYCHOLOGICAL CONTEXT)** (DEPRESSION, SLEEP, WELLBEING) <CATEGORICAL> and [SLEEP, PHYSI, TALK] <DURATION, MEAN, VAR>.
Zhai & Barreto (Zhai & Barreto, 2006)	(TEMP, LIGHT) <INTENSITY>.	**(PHYSIOLOGICAL CONTEXT)** (PUPIL) <DIAMETER> [-NOISE [FAKEDATA]] <MEAN>, (BVP(IBI)) <PSD <LF/HF>, MEAN, STD, AMP>, [EDA] <COUNT, MEAN, AMP, RISETIME, POWER> and [ST] <SLOPE, MEAN>.

() represents a raw signal; {} an instrument; [] a preprocessed signal; and <> an extracted property.

5.5. ANALYSIS

The following table summarizes the extracted properties identified in each investigation in this literature review.

After the pre-processing phase follows the extraction of properties that may contain emotional content (Jerritta et al., 2011). These properties can be seen as replacement or additional input to the original dataset, and can be extracted directly from the signal collected from context or from the already preprocessed signal (Haag et al., 2004). The strategy followed in extracting properties is related to the performance of the algorithms (Matlovic et al., 2016) (Adams & Robinson, 2015) (Lisetti & Nasoz, 2004).

This section of extracted properties focuses primarily on context-specific properties because of their possible relation to the efficiency of classifiers in automatic emotion detection (Matlovic et al., 2016). The strong presence of generic properties (e.g. mathematical, signal analysis), motivated us to start with a summary presentation of these properties widely used by researchers. However, despite the possibility of using these generic properties not used in the investigations under review, it is intended to keep the focus on context-specific properties as it is believed to be the type of properties that could most lead to an increase in the accuracy of the algorithm results.

Research using facial expression, speech, and body posture for emotion detection uses many descriptors as extracted properties (e.g. LBP, LPQ, GABOR, MFC), and few extract properties from other modalities simultaneously. However, emotions can be decoded from other extracted properties (e.g. POSITION and ANGLE from the context variables HANDS, HEAD, SHOULDERS, and SPIN) (Saha et al., 2014). MEAN, STD, MAX, MIN, COUNTOUR and POWER, are properties that are widely used in the context of SPEECH (Dellaert, Polzin, & Waibel, 1973) (Busso et al., 2004).

There are many researchers who extract properties from physiological context data. Although few do it from several modalities simultaneously, these researchers are the ones who diversify the choice of extracted properties the most (e.g. Jaques et al. (Jaques et al., 2015), Soleymani et al. (Soleymani et al., 2013), Sano & Picard (Sano & Picard, 2013b), etc.). The diversity of extracted properties is greater when the data originates from brain activity (e.g. ALPHA, BETA, THETA, DELTA, etc.), muscle activity (e.g. EMGCOR, EMGZYG, SMILING, FROWNING, etc.), eye activity (e.g. EOGV, EOGH, SACCADE, DILATION, FIXATION, etc.) and heart activity (e.g. PNNX, HRVI, TINN, SDNNI, etc.). Note the existence of several levels of abstraction of extracted properties that diversify information closer to the source data and other closer to the meaning for humans (e.g. in muscle activity properties are extracted that mean SMILING and FROWNING but based on a lower level of properties, i.e. EMGCOR and EMGZYG activity).

There are still not many investigations that extract properties related to social and psychological context. However, when they do, they diversify by presenting a greater amount of context-specific properties (e.g. Santo & Eng (Sano & Eng, 2016), Jaques et al. (Jaques et al., 2015), Sano & Picard (Sano & Picard, 2013b), Bogomolov et al. (Bogomolov et al., 2014), LikamWa et al. (LiKamWa et al., 2013), Bauer & Lukowicz (Bauer & Lukowicz, 2012), etc.). This diversity of properties extracted from the data coming from the social and psychological context supports the hypothesis that it is possible to create a more efficient emotional detection system if the input of the algorithms contains more information from this modality. Although the increase in the number of properties extracted in all modalities is noticeable over time, the gradation is more evident in those extracted from social and psychological context data. This diversification in recent research shows the interest of researchers in correlating properties extracted from this context, supporting the hypothesis that they can be an important input for an emotional classifier.

Many researchers collect context data through questionnaires (e.g. EMOTIONS, MOOD, STRESS, etc.). Although widely used in the literature under review, it is not always clear what statistical properties can be extracted from the analysis of these data, which motivated us to group in the CATEGORICAL token the set of possible properties to extract from these instruments.

RESEARCH	EXP. FACIAL, ORAL AND BODY POSTURE	CONTEXT PHYSIOLOGICAL	SOCIAL CONTEXT AND PSYCHOLOGICAL	OTHER
Perdiz et al. (Perdiz et al., 2017) e (Phinyomark et al., 2012)	(HEAD) <ANGLE>.	(EMG) <WL, WAMP, AR, MAV, MAVS>, [EMG] <<EMGCOR, EMGZYG> <MAX, MIN>> and (EOG) <SACCADE <THRESHOLD, MAX>>.		
S. H. Lee et al. (S. H. Lee et al., 2016)	[FACS (EYEBROWS, EYELIDS, NOSE, LIPS, WRINKLES, LIPS, CHEEKS, JAW, MOUTH)] <LBP, LPQ, GABOR, DISTANCE, SHAPE, CLUSTERS <CENTROID>, DISPLACEMENT>.			{HAC}.
Eckert et al. (Eckert et al., 2016)	[FACS, CAAU] <THRESHOLD, SHAPE <AREA, DISTANCE>>.			
Matlovic et al. (Matlovic et al., 2016)		(EEG) <<ALPHA, BETA> <STRENGTH, SUBTRACT, POWER, MEAN, RATIO>>.		
Gogia et al. (Gogia et al., 2016)	(HEAD) <ANGLE <TIMING>>.	[EEG] <THRESHOLD, MEDITATION, ATTENTION>.		
Z. Zhang et al. (Z. Zhang et al., 2016)	(HEAD) <GABOR>, [HEAD] <POSITION, ANGLE <STD>> and [FACS] <SHAPE>.		[EMOTIONS] <CATEGORICAL>.	
Sano & Eng (Sano & Eng, 2016)		(EEG) <PSD <PERIODS <<ALPHA, BETA, THETA, DELTA>>, AMP <MEAN, STD, MEDIAN>>, [EDA] <THRESHOLD, PKF <MEAN, STD, MEDIAN>> and [EDA] and (ST) <PERIODS <ADL <AMP <MEAN, MEDIAN, STD>>>>.	(AGE, PERSON, ACADGR) <MEAN, MEDIAN, STD>, (STRESS, HEALTH, ANEXIETY, ACADDG, ACADCL, ACADGR, MOOD, HAPPY, ALERT, ENERGY, CALM, PERSON) <<MOTORICAL <MEAN, MEDIAN, STD>, (PHYSI <CATEGORICAL <DURATION>, (SLEEP>, (SLEEP)CATEGORICAL <MEAN, MEDIAN, STD>>, (PHYSI)	[ACC] <MEAN, STD, MEDIAN, MAG <THRESHOLD>, MOTION <LEVEL>, <MEAN, STD>>, [ACC [ADL]] <PERIODS <COUNT, MEAN, MEDIAN, STD>> and (LIGHT) <PERIODS <MEAN, STD>>.

			<CATEGORICAL <DURATION>>, (SLEEP) and [ACC] <<MOTION <LEVEL>> <SLEEPKIND>>, [SLEEP] <<WAKEUPKIND, DURATION, COUNT, TIMING, REGULARITY, LATENCY, AWAKENINGS> <MEAN, MEDIAN, STD>>, (NAP) <DURATION, COUNT>, (EMAIL) <<OUTGOING, INCOMING, INTERLOCUTORS> <PERIODS <COUNT, MEAN, STD> <DURATION, TIMING <MEAN, MEDIAN, STD>, INTERLOCUTORS <OUTGOING, INCOMING> <COUNT>, (SMS) <TIMING <MEAN, MEDIAN, STD>, COUNT, INTERLOCUTORS, INCOMING, PERIODS <OUTGOING <COUNT> <COUNT>, (SOCIAL, FTF) <<AFFINITY, <INTERACTIONS <QUALITY> <COUNT, TIMING, REGULARITY>>, (SCREEN) <COUNT, TIMING, PERIODS <DURATION>, (LOCAL) <PERIODS <DISTANCE <MEDIAN, STD><>, (CAFFEI) <LASTTIME>, (ACADST, ACADEX) <DURATION> and (ACADCL) <<CLASSROOM, ONLINECLASS, SEMINAR, LAB, GROUPWORK> <DURATION>.	
Zhao et al. (Zhao et al., 2016)		[IBI] <SDNNI, PNNX, HRVTI, TINN, HR <MEAN, STD>, PSD <LF/HF>, POINCARE <STD>, ENTROPY, DFA> and [RESP] <PKF, MEAN, MEDIAN, PSD <PLF, PHF>, POINCARE <STD>, DFA>.	[EMOTIONS] <CATEGORICAL>.	
Zenonos et al. (Zenonos et al., 2016)		[IBI] <MEAN, STD, PNNX, HRVI, TINN, POINCARE <STD>>, [IBI [BANDS]] <PSD <LF/HF>> and (HR) <ENTROPY, DFA>.	(MOOD, EMOTIONS) <CATEGORICAL>.	

Basu et al. (Basu et al., 2016)		(EMG) <EMGCOR, EMGZYG>, (ECG, HR, PR, RESP(RR), EDA, ST, EMG <EMGCOR, EMGZYG>) <MEAN, STD, MAV1D, MAV2D> and [ECG, HR, PR, RESP(RR), EDA, ST, EMG <EMGCOR, EMGZYG>] <MAV1D, MAV2D>.		
Aracena et al. (Aracena et al., 2016)		(PUPIL) <DIAMETER>, [PUPIL] <DILATION <DIAMETER>, SIZE <MEAN>> and [GAZE] <DIRECTION>.		
Adams & Robinson (Adams & Robinson, 2015)	(HEAD) <ANGLE> and [FACS (EYEBROWS, CHEEKS, EYELIDS, CHEEKS, NOSE, WRINKLES, LIPS, JAW, EYES, HEAD, CHIN)] <INTENSITY>.	(GAZE) <DIRECTION>.		
Turan et al. (Turan et al., 2015)	(FACE) <LBP, LPQ, WLD, PHOG> and (EYES) <DISTANCE>.			
Korkmaz & Atasoy (Korkmaz & Atasoy, 2015)	(VOLUME) <MEAN, MEDIAN, SKEWNESS, KURTOSIS, MAX, MIN, AMP> and [SPEECH [INTERVALSPLIT, DY/DX, D Y/DX^{22}]] <MFCC <MEAN, MEDIAN, SKEWNESS, KURTOSIS, MAX, MIN, AMP, ZCR>>.			
Lalitha et al. (Lalitha et al., 2015)	(SPEECH) <TEAE, DWTC, LPCC, MEDC, SHIM, SPRO, SPFL, SPCE, HNR, ZCR>.			
Singh et al. (Singh et al., 2015)	[SHOULDERS, HANDS] <SINGH, SLOPE, ANGLE>.			
Murali et al. (Murali et al., 2015) e (Padmanabhan et al., 2015)		[((ECG, ICG)(PEP, PTT), ICG, NIBP, RESP(RR), EDA] <MEAN, MEDIAN, STD>.		
Jaques et al. (Jaques et al., 2015)		(EDA) [RAW, FINALRAW, DY/DX] <PERIODS <MEAN, MAX, MIN>>, [EDA [DY/DX]] <THRESHOLD, AMP, DURATION, SHAPE, PERIODS <COUNT>, INTEGRAL, RISETIME> and [ST] <PERIODS>.	(SOCIAL, CAFFEI, ALCOH, DRUGS) <CATEGORICAL>, (CALL, SMS, SCREEN) <STD>, (CALL, SMS, SCREEN) <PERIODS <MEAN, MEDIAN>, (CALL, SMS, SCREEN, ACADCL, PHYSI, ACADEX) <COUNT>, (CALL, SCREEN, ACADCL,	(ACC) <MAG> and [ACC] <PERIODS>.

			PHYSI, ACADEX, ACADST) <DURATION>, (SLEEP, NAP) <PERIODS <DURATION>, (CALL, SMS) <TIMING, <INCOMING, OUTGOING, INTERLOCUTORS> <COUNT>, (LOCAL) <<LATITUDE, LONGITUDE> <MEDIAN> and [LOCAL [PATHSTAKEN]] <DISTANCE>.	
Cruz et al. (Cruz et al., 2015)		[EOG] <<EOGH, EOGV> <THRESHOLD, MAX, MIN, MEAN, AMP>>.		
Saha et al. (Saha et al., 2014)	[HEAD, SHOULDERS, HANDS, WRISTS, ELBOWS, SPIN] <POSITION, ANGLE, DISTANCE>.			(ACC) <MAX, SPEED <SUBTRACT <DISPLACEMENT> >>.
Matiko et al. (Matiko et al., 2014)		(EEG) <HEMISPHERE <LEFT, RIGHT>, ALPHA <MEAN, STD, MAV1D, MAV2D, POWER>>.	(EMOTIONS) <CATEGORICAL>.	(EEG) <MATIKO>.
Bogomolov et al. (Bogomolov et al., 2014)			(STRESS) <CATEGORICAL <SKEWNESS, KURTOSIS>>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <<INCOMING, OUTGOING, MISSEDCALL> <COUNT>>, (CALL) <INTERLOCUTORS <OUTGOING, INCOMING, MISSEDCALL> <COUNT, ENTROPY>>, (CALL) <RATIO <INTERLOCUTORS <CALL, SMS, PROXIMITY>>, (SMS) <INCOMING, OUTGOING <COUNT>>, (SMS) <INTERLOCUTORS <INCOMING, OUTGOING> <COUNT, ENTROPY>>, (SMS) <RATIO <INTERLOCUTORS <CALL, SMS, PROXIMITY>>>, (CALL) <PERIODS <INCOMING, OUTGOING>>, (CALL,	(WEATHER) <PERIODS <TEMP <MEAN>, PRESSURE, PRECIPITATION, HUMIDITY, VISIBILITY, WIND <SPEED><SPEED>.

			SMS) <INITIATEDONLY <PERIODS <<COUNT>>, ELAPSEDTIME <MEAN, VAR>>, [SMS] <ANSWER <RATIO, LATENCY>>, (CALL, SMS) <PERIODS <MEAN, MEDIAN, MIN, MAX, QUANTILE, STD, VAR>> and (PROXIMITY) <DEVICES <ELAPSEDTIME <MEAN, VAR>, ENTROPY>, PERIODS <USUAL <COUNT> <COUNT>.	
Agrawal et al. (Agrawal et al., 2013)	[EYES, LIPS] <CENTROID <AREA>, CORRELATION <THRESHOLD>>.			
Soleymani et al. (Soleymani et al., 2013)	[HEAD] <POSITION>, [EYES] <IRIS <MEAN>, [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <DISTANCE>, [EYES, EYEBROWS, LIPS] <EYECORNERS <MEAN, ANGLE>> and [LIPS, MOUTH] <DISTANCE>.	(EEG) <PSD <THETA, ALPHA, BETA, GAMMA>, SUBTRACT <PSD <HEMISPHERE <LEFT, RIGHT>>>> and (EEG) and [HEAD, EYES, NOSE, EYEBROWS, LIPS, MOUTH] <CORRELATION, MEAN, STD>.	(EMOTIONS) <CATEGORICAL>.	
Vermun et al. (Vermun et al., 2013)	[HEAD] <MOTION, ANGLE>, [LIPS] <LIPSPUCKER>, [MOUTH] <MOUTHOPENING>, (EYEBROWS) <BROWSRAISING>, [ARMS] <CROSSEDARMS>, [HIP, SHOULDERS, KNEES] <ERECTBACK, SITTINGPOSTURE <LEFT, RIGHT, CENTER> and [HIP, KNEES] <CENTER <ANGLE>.			
Kusserow et al. (Kusserow et al., 2013)		[HR] <MAX>.	(MOOD, STRESS) <CATEGORICAL>.	(ACC) <MOTION>.
Alzoubi et al. (Alzoubi et al., 2013)		(EMG) <EMGCOR, EMGZYG>, (ECG(HRV), RESP, EDA, EMG <EMGCOR, EMGZYG>) <MEAN, MEDIAN, STD, MAX, MIN, AMP>, (EDA) <RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MIN>, RATIO <1DIFF, MAX>, (EMG	(EMOTIONS) <CATEGORICAL>.	{AUBT}.

		<EMGZYG>) <RATIO <1DIFF, MAX>, RATIO <1DIFF, MIN>, SUBTRACT <2DIFF, MEAN>, RATIO <2DIFF, MIN>, RATIO <2DIFF, MAX>, and (RESP) <SUBTRACT <2DIFF, MIN>, SUBTRACT <AMP, 2DIFF, MAX>, RATIO <2DIFF, MAX>, RATIO <1DIFF, MAX>.		
Nawasalkar et al. (Nawasalkar et al., 2013)		[NIBP] <MEAN>.		
Sano & Picard (Sano & Picard, 2013b)		[EDA] <SLOPE <THRESHOLD <COUNT>>> and [EDA] <PERIODS <AMP <MEAN, STD, MEDIAN>>>.	(SCREEN) <PERIODS <COUNT, STD>>, (LOCAL) <<DISTANCE, RADIUS> <MEDIAN, STD>>, (SLEEP) <<DURATION, TIMING, QUALITY> <MEAN, STD, MEDIAN>>, (SLEEP) <SLEEPCONDITIONERS>, (ELECTR) <<USAGE <LASTTIME> <MEAN, STD, MEDIAN>>, (HEALTH, MOOD, ALERT, TIRED, STRESS) <<LEVEL <PERIODS, TIMING>> <MEAN, STD, MEDIAN>>, (NAP) <TIMING, DURATION>, (CAFFEI) <<COUNT> <MEAN, STD, MEDIAN>>, (ALCOH) <<LASTTIME, COUNT, TIMING> <MEAN, STD, MEDIAN>, (PERSON) <EXTRAVERSION, NEUROTICISM, AGREEABLENESS, CONSCIENTIOUSNESS, OPENNESS>, (CALL) <PERIODS <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INCOMING, OUTGOING> <TIMING, DURATION, COUNT, RATIO> <MEAN, STD, MEDIAN>>, (CALL) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>, (CALL) <<MISSEDCALL <MEAN, STD, MEDIAN>>, RATIO <MISSEDCALL <OUTOING,	(ACC) <PERIODS <MEDIAN, STD>> and (ACC) <PERIODS <MOTION <LEVEL <MEAN>>>>.

			INCOMING>>, (SMS) <PERIODS <<TIMING, SIZE, COUNT, RATIO> <MEAN, STD MEDIAN>>>, (SMS) <<SIZE <INCOMING, OUTGOING>> <MEAN, STD, MEDIAN>> and (SMS) <<INTERLOCUTORS> <MEAN, STD, MEDIAN>>.	
Raudonis (Raudonis, 2013)		[PUPIL] <DIAMETER <MIN, MAX>, LOCATION <THRESHOLD> and (EYES) <MOTION <SPEED>>.		
Kawai et al. (Kawai et al., 2013)		[PUPIL] <DIAMETER, AREA, MOTION, LOCATION>.	(EMOTIONS) <CATEGORICAL>.	
Babiker et al. (Babiker et al., 2013)		[PUPIL] <DIAMETER <DILATION, MEAN, STD>>, (EYES) <MOTION> and (GAZE) <SACCADES, FIXATION>.	(EMOTIONS) <CATEGORICAL>.	
LikamWa et al. (LiKamWa et al., 2013)			[MOOD] <PERIODS <COUNT, STD <MEAN, MAX>>, (EMAIL, SMS) <INTERLOCUTORS <USUAL <COUNT, SIZE>>>, (CALL) <INTERLOCUTORS <USUAL <COUNT, DURATION>>, (APPS) <COUNT, DURATION> and (BROWSER, LOCAL) <COUNT>.	
Murad & Malkawi (Murad & Malkawi, 2012)		(EEG) <ALPHA, BETA THETA, DELTA>.		
C. Y. Chang et al. (Chang et al., 2012)		[BVP] and [ECG, BVP, PR] <MAX>.	(EMOTIONS) <CATEGORICAL>.	
Bauer & Lukowicz (Bauer & Lukowicz, 2012)			(LOCAL) [USUALPLACES] <DIAMETER <MAX>, DURATION <MEAN, THRESHOLD>>, [LOCAL] <ROI <TIMING, REGULARITY, COUNT <MEAN, AD, STD>>>, (PROXIMITY) <TIMING, DURATION <THRESHOLD, AD, MEAN, STSD>, COUNT <AD, MEAN, STD>> and (CALL, SMS) <<INCOMING,	

			OUTGOING> <INTERLOCUTORS <COUNT <MEAN, STD>>, COUNT <AD, MEAN, STD>>>.	
Yang & Bhanu (S. Yang & Bhanu, 2011)	[HEAD, FACE] <LBP, LPQ>.			
Dhall et al. (Dhall et al., 2011)	[FACE] <LPQ, PHOG>.			
Mokhayeri & Toosizadeh (Mokhayeri & Toosizadeh, 2011)		[ECG(HRV)] <PSD, MEAN, MIN, MAX, VAR, STD, SKEWNESS>, (PPG) <MEAN, VAR, STD, SKEWNESS, KURTOSIS> and [PUPIL] <DILATION, DIAMETER <MEAN, MAX, KURTOSIS>.		
Hernandez et al. (Hernandez et al., 2011)		[EDA] [PEAKDETECT] <MEAN> and [EDA] <MEAN, DURATION, MAX, MIN, STD, SLOPE, ZEROCROSSINGS <COUNT>, QUANTILE <THRESHOLD>>.	(STRESS) <CATEGORICAL>, (CALL) [LABELING] <COUNT, MEAN, DURATION, MAX, MIN, STD, SLOPE, ZEROCROSSINGS <COUNT>, QUANTILE <THRESHOLD>>.	
N. Lane et al. (N. Lane et al., 2011)			(DEPRESSION, SLEEP, WELLBEING) <CATEGORICAL> and [SLEEP, PHYSI, TALK] <DURATION, MEAN, VAR>.	(ACC) <MEAN, VARIANCE, PERIODS <MOTION <COUNT, DURATION>>.
H. Wang et al. (H. Wang et al., 2010)	[EYES] <STATUS, THRESHOLD, LBP, PERIODS <RATIO <STATUS, DURATION>>>.			
Bos (Bos, 2010)		[EEG] <ALPHA, BETA, RATIO <BETA, ALPHA>, POWER <ALPHA>, POWER <BETA>, POWER <ALPHA, BETA>, RATIO <BETA, POWER <ALPHA>, RATIO <POWER <BETA>, POWER <ALPHA>.		
Y. Liu et al. (Y. Liu et al., 2010)		(EEG) <ALPHA, THETA, BETA, DELTA, GAMMA> and (EEG) [FD] <MEAN, HEMISPHERE <LEFT, RIGHT>, THRESHOLD>.	(EMOTIONS) <CATEGORICAL, LEVEL>.	

Setz et al. (Setz et al., 2010)		(EDA) [PEAKDETECT] <RATIO <COUNT, DURATION>, HEIGHT <MEAN>, TIMING, QUANTILE <THRESHOLD>> and [EDA] <PHASES <LEVEL <MEAN, MAX, MIN, SLOPE>>>.		
J. Kim & Andre (J. Kim & André, 2008)		(ECG(HR, HRV)) [FOURIER [BANDS]] <POWER <MEAN, LF/HF>, MAG <MAX>, (ECG) [PEAKDETECT] <ENTROPY>, [ECG(HRV)] <N-N <MEAN, STD, COUNT>, 1DIFF <STD>, RATIO, R-R <POINCARE, STD>, ENTROPY>, [ECG(HRV)] [BANDS] <PSD <POWER, DMF>, LF/HF>, (RESP (RR, BRV)) [BANDS] <POWER <MEAN>, MAG <MAX>, (RESP (RR)) <MEAN> [LPF] <ZEROCROSSINGS <COUNT>, (RESP (BRV)) <MEAN, STD, 1DIFF <STD>, POINCARE>, (RESP (BRV)) [BANDS] <PKF, POWER, RATIO <POWER, BANDS>>, [EDA] <MEAN, STD, ZEROCROSSINGS <COUNT>, MAX>, [EDA] [DY/DX, D2Y/DX2] <MEAN>, (EMG) <MEAN> and [EMG] <STD>.		
Lichtenstein et al. (Lichtenstein, Antje; Oehme, 2008)		(ECG(HRV)) <PNNX>, (ECG(HR, HRV, IBI)) <LF/HF>, (RESP(RR)) <AMP>, (RESP(RDEP)) <COUNT, THRESHOLD>, [EDA] <MEDIAN, AMP, DURATION>, (EDA) [LPF] <TPOINTS <COUNT>, CHANGES>, (EMG) <<EMGCOR, EMGZYG> <CONTRACTIONS <COUNT>, MUSCLE <CHANGES>, STD>> and (ST) <MEAN, CHANGES>.	(EMOTIONS) <CATEGORICAL>.	

Margaret M. Bradley et al. (Margaret M. Bradley et al., 2008)		[PUPIL] <DIAMETER <CHANGES, MEAN, AMP, MAX>>, [EDA] <MAX, VAR> and (ECG(HR, IBI)) <PERIODS <MEAN>>.		
Gunes & Piccardi (Gunes & Piccardi, 2007)	[LIPS] <LIPEBITE, LIPEWIPE, STATUS, LIPSPUCKER>, [MOUTH] <MOUTHSTRETCH, STATUS, MOUTHCORNERS>, [EYES] <MOTION, SPEED, WRINKLEDEYES>, [EYEBROWS] <BROWSRAISING, SHAPE>, [EYELIDS] <POSITION, WRINKLEDEL>, [CHEEKS, JAW] <POSITION>, [NOSE] <WRINKLEDNOSE>, [FOREHEAD] <WRINKLEDLEDFH>, [HANDS, PALMS] <POSITION>, [FINGERS] <MOTION, FINGERTAPPING, POSITION>, [HANDS, FISTS] <STATUS>, [SHOULDERS] <MOTION> and [SHOULDERS, HANDS, FINGERS, FISTS, PALMS, NECK] <CONTROID, AREA, RATIO <DILATION>.			
Castellano et al. (Castellano et al., 2007)	(ARMS) <MOTION <QUANTITY, MAX, MIN>, SPEED, DISPLACEMENT, SLOPE, AMP, ACC, MAINPEAK <SLOPE, MAX, MIN>, MAX, MEAN, RATIO <MEAN, MAX>, RATIO <MAX, MAINPEAK <DURATION>, RATIO <MAINPEAK <DURATION>, DURATION>, POWER <CENTROID>, DISTANCE <MAX, CENTROID>, MAX <POSITION>.			
Mandryk & Atkins		[EDA] <MIN, MAX>, [EMG] <SMILING,	(EMOTIONS) <CATEGORICAL>.	

(Mandryk & Atkins, 2007)		FROWNING> and [ECG(HR), EDA, EMG] <MEAN, STD>.		
Sebe et al. (Sebe et al., 2006)	[HEAD] <MOTION <DIRECTION, INTENSITY>>, [SPEECH] <SPEED> and [PITCH] <MAX>.			
Zhai & Barreto (Zhai & Barreto, 2006)		(PUPIL) <DIAMETER> [-NOISE [FAKEDATA]] <MEAN>, (BVP(IBI)) <PSD <LF/HF>, MEAN, STD, AMP>, [EDA] <COUNT, MEAN, AMP, RISETIME, POWER> and [ST] <SLOPE, MEAN>.		(TEMP, LIGHT) <INTENSITY>.
J. A. Healey & Picard (J. A. Healey & Picard, 2005) e (Rosalind W. Picard et al., 2001)		[EDA] <PERIODS <MAG <SUM>, DURATION <SUM>, INTEGRAL <SUM>, MEAN, VAR>, (EDA) [PEAKDETECT] <COUNT>, [EMG] [NORM] <MEAN, VAR>, [RESP] <VAR, MEAN>, (RESP) [BANDS] <PSD <POWER <MEAN>, (ECG(HR)) <LF/HF, MEAN>, (ECG(HRV)) <PERIODS <LF/HF, LFMF/HF>, MEAN> and [EDA, EMG, RESP, ECG(HR, HRV) and [STRESS] <COVAR, STD>.	[STRESS] <LEVEL <PERIODS <MEAN, STD>>.	
Herbon et al. (Herbon et al., 2005)		(PUPIL) <DILATION> and (HR, EDA, ST, PUPIL) <STD <THRESHOLD>.	(EMOTIONS) <CATEGORICAL <STD>>.	
Partala et al. (Partala et al., 2005)		[EMG] <<EMGZYG <SMILING>, EMGCOR <FROWNING> <MEAN>.	(EMOTIONS) <CATEGORICAL>.	
Van Eck et al. (van Eck et al., 2005)		[CORT] <TIMING, MEAN, SLOPE, VAR, COVAR, STD>.	(LIFEEVENTS, DIFFICULTIES, HEALTH, DEPRESSION, ANXIETY, ANGER, MOOD, WELLBEING, STRESS, EMOTIONS) <CATEGORICAL> and (STRESS) <STD, MEAN, TIMING, UNPLEASANTNESS, IMPORTANCE, PREDICTABILITY, CONTROLLABILITY, LASTSTRESS>.	

Busso et al. (Busso et al., 2004)	(PITCH, VOLUME) <MEAN, STD, MAX, MIN, MEDIAN> and [FOREHEAD, EYEBROWS, EYES, CHEEKS] <CLUSTERS, AREA>.			
Lisetti & Nasoz (Lisetti & Nasoz, 2004)		[HR, EDA, ST] <MIN, MAX, MEAN, VAR>.	(EMOTIONS) <CATEGORICAL>.	
K. H. Kim et al. (K. H. Kim et al., 2004)		[ECG(HRV)] <MEAN, STD, DY/DX>, (EDA) <MEAN, ZEROCROSSINGS <COUNT>, MAX, AMP, DURATION> and [EDA] <DY/DX>.	(EMOTIONS) <CATEGORICAL>.	
Haag et al. (Haag et al., 2004)		[ECG(HR)] <MIN, MAX, MEAN, STD>, [PPG(BVP(HR))] <MIN, MAX, AMP, STD, RATIO <SUM>, [EDA] <SLOPE, MEAN, STD>, [RESP] <SLOPE, MEAN, STD, AMP <STD>, SPEED <STD>, [EMG] <SLOPE, MEAN, STD, AMP> and (ST) <SLOPE, MEAN, STD>.		
Partala & Surakka (Partala & Surakka, 2003)		[PUPIL] <DIAMETER, DILATION <MEAN>, FIXATION, VAR>.	(EMOTIONS) <CATEGORICAL>.	
C J Harmer et al. (C J Harmer et al., 2003)		(SEROT) <TIMING, LEVEL, VAR, MEDIAN>.	(MOOD, ENERGY, EMOTIONS, ANXIETY) <CATEGORICAL>.	
Nwe et al. (Nwe et al., 2001)	[SPEECH] <MFCC <POWER>>.			
Buchanan & Lovallo (Buchanan & Lovallo, 2001)		(CORT) <MEAN>.	(EMOTIONS) <CATEGORICAL>.	
Jennifer a Healey et al. (Jennifer a Healey et al., 2000)		[ECG(HR, HRV), EDA, EMG] <MEAN, VAR, 1DIFF <MEAN>, SLOPE>, [EMG] <PERIODS <MEAN>, [EDA] <PERIODS <MAX, MIN>>, [PPG(BVP(HR))] <MEAN, 1DIFF <MEAN>> and [RESP] <MEAN, VAR, PSD>.	(STRESS) <CATEGORICAL>.	
Vrijkotte et al. (Vrijkotte et al., 2000)		[ECG(HR, IBI(RMSSD))] <<PERIODS, TIMING, DURATION> <MEAN, STD>>.	(STRESS) <EFFORT, REWARD, OVERCOMMITMENT, RATIO <EFFORT,	

			REWARD>, (PHYSI) and (ACC) <MOTION>, (CAFFEI, ALCOH, SMOKING) <COUNT>, (MOOD) <LEVEL> and (PERSON) <CATEGORICAL>.	
Ritz et al. (Ritz et al., 2000)		[BP(SBP)] <CHANGES> and [HR, BP(SBP, DBP), ROS, RR, VT, EDA] <MEAN, STD>.	(EMOTIONS) <CATEGORICAL>.	
L. S. Chen et al. (L. S. Chen et al., 1998)	[PITCH] <CONTOUR <MAX, MIN, MEAN, STD, THRESHOLD>>, (SPEECH) <RMS <POWER>> and (PITCH) <CONTOUR> [DY/DX] <MAX, MIN>.			
J. Healey & Picard (J. Healey & Picard, 1998)		[EMG] <PHASES <MUSCLE <MEAN>>, [EDA] <PHASES <MEAN, 1DIFF <SLOPE <MEAN>>>>, (PPG(BVP(HR))) <PHASES <MEAN, 1DIFF <CHANGES <MEAN>>>> and [RESP] <MEAN, VAR, PSD>.		
Rajita Sinha (Rajita Sinha, 1996)		(EOG) <QUANTILE <MOTION>, MEDIAN>, [ECG(HR), BP(SBP, DBP), EDA, EOG] <PERIODS <MEDIAN>>, (ST, EMG) <PERIODS <MEDIAN>> and (BP(DBP)) <CHANGES>.	(EMOTIONS) <CATEGORICAL>.	
Scott R. Vrana (Scott R. Vrana, 1993)		[EMG] <<EMGCOR, EMGZYG, LEVATOR> <PERIODS <TENSION>>>, [ECG(HR)] <CHANGES> and (EDA) <PERIODS <MEAN>>.	(EMOTIONS) <CATEGORICAL>.	
R Sinha et al. (R Sinha et al., 1992)		[ICG(SV, CO, PVR, PEP, LVET), ECG(HR), BP(SBP, DBP)] <CHANGES <MEAN, STD>, PERIODS <MEAN> <MEAN> and [BP(SBP, DBP)] <MEAN>.	(EMOTIONS) <CATEGORICAL>.	

() represents a raw signal; {} an instrument; [] a preprocessed signal; and <> an extracted property.

6. CONCLUSION

The number of investigations related to Affective Computing (AC) has been increasing in recent years and is expected to continue to grow in the coming years. This probability motivated the authors to design this technical report so that it could be supplemented with new information flexibly and quickly when new iterations are made to update the state of the art of automatic emotion detection.

The main concern of the authors when designing the structure of this technical report was to allow for the systematic, synthetic, and organized registration of the information obtained from the review of the state of the art in the area of AC. The strategy was to: i) anchor the information obtained to representative sections of the different steps of the generic model used in the emotional research (Figure 1); and ii) cataloging this information in summary tables using tokens representative of the content, to facilitate the search and reading of the processed information.

This systematic organization of information facilitates the recording of the knowledge obtained by reading the various investigations analyzed. It easily allows the inclusion of new context variables and domain properties, new instruments & sensors, new pre-processing techniques and new extracted properties. As each investigation is analyzed, its content is dissected and catalogued in summary tables. The result is a tool that allows you to document and analyze the content processed in the various investigations.

Besides being able to grow in width with the analysis of more investigations, it is also intended to improve it in the vertical component. In this first version we have not considered the last stages of the generic model proposed by the authors for emotional research. So, in the future, we intend to include a section to also systematize the information about the classification algorithms used by the researchers, and a section to summarize the instruments through which the researchers represent the classified emotions. There is also the will to include an appendix with summary tables with the emotional provocation instruments used in the investigations (e.g. audio, video).

This literature survey served as a support for the preparation of the authors' experience in the area of AC. We intend to verify the hypothesis that it is possible to detect well-being in office workers, based on a multimodal collection of context variables. The knowledge obtained from this literature survey will allow us to plan an experiment to collect a dataset in a real environment. We will collect several variables of philological, social, and religious context from several participants, office workers from several organizations.

Organizations are increasingly dynamic and demanding with their workers. The stress related to the agglomeration of tasks and meeting deadlines often makes the workplace an aggressive environment where negative emotions are experienced. However, personal fulfillment resulting from recognition by others, good team spirit, and meeting goals may help to counterbalance these positive emotions (e.g. achievement of business, turnover, meeting deadlines, etc.). The motivation of the authors in studying the emotional environment of offices results from: i) the need to study the environment in which people work based on the monitoring of its context variables; and ii) the close professional connection that the authors have with the business world.

The authors are convinced that it will be possible to create more affectively intelligent office systems so that the well-being of their workers can be improved in the future.

7. BIBLIOGRAPHY

4iiii Innovations Inc. (2018). I Love Viiiiva. Retrieved January 28, 2018, from https://4iiii-innovations.myshopify.com/collections/heart-rate-monitors

Aaron T. Beck (1967). *Depression:Clinical, Experimental, and Theoretical Aspects*. Philadelphia: University of Pennsylvania Press.

Aboy, M., Cuesta-Frau, D., Austin, D., & Mico-Tormos, P. (2007). Characterization of sample entropy in the context of biomedical signal analysis. *Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, *2007*, 5943-5946. https://doi.org/10.1109/IEMBS.2007.4353701

Adams, A., & Robinson, P. (2015). Automated recognition of complex categorical emotions from facial expressions and head motions. *2015 International Conference on Affective Computing and Intelligent Interaction, ACII 2015*, 355-361. https://doi.org/10.1109/ACII.2015.7344595

Adhikari, P. R. (2016). How is chi test used for feature selection in machine learning? Retrieved October 29, 2017, from https://www.quora.com/How-is-chi-test-used-for-feature-selection-in-machine-learning

ADInstruments (n.d.-a). ADInstruments FE116 GSR Amp (FE116-DCW-15A).

ADInstruments (n.d.-b). ADInstruments ML135 Dual Bio Amp (ML135-DC-05A).

ADInstruments (n.d.-c). ADInstruments ML309 Thermistor Pod (ML309-DCW-15A).

ADInstruments (n.d.-d). ADInstruments ML870 PowerLab 8/30 (ML870-DC-05A).

ADInstruments (n.d.-e). LabChart for Research | ADInstruments. Retrieved June 12, 2017, from https://www.adinstruments.com/products/labchart/labchart-for-research

Affectiva Inc (2013). Affectiva Q User manual.

Affectiva Inc. (2014). Q Sensor 2.0 Datasheet 2.0.

Affectiva Inc (2017). Affectiva | Emotion as a Service. Retrieved August 16, 2017, from https://www.affectiva.com/product/emotion-as-a-service/

Agrawal, U., Giripunje, S., & Bajaj, P. (2013). Emotion and gesture recognition with soft computing tool for drivers assistance system in human centered transportation. *Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013*, 4612-4616. https://doi.org/10.1109/SMC.2013.785

Aharony, N., & Gardner, W. (2011). Funf: Open Sensing Framework. Retrieved April 23, 2016, from http://www.funf.org

Ahlstrom, C., Johansson, A., Uhlin, F., L?nne, T., & Ask, P. (2005). Noninvasive investigation of blood pressure changes using the pulse wave transit time: A novel approach in the monitoring of hemodialysis patients. *Journal of Artificial Organs*, *8*(3), 192-197. https://doi.org/10.1007/s10047-005-0301-4

Alabdulkarim, A. (2015). Towards hand-gesture frustration detection in interactive systems. *Proceedings - 2014 3rd International Conference on User Science and Engineering: Experience. Engineer. Engage, i-USEr 2014*, 153-157.

https://doi.org/10.1109/IUSER.2014.7002694

Algorithmia. (2017). SpreadSubsample. Retrieved October 29, 2017, from https://algorithmia.com/algorithms/weka/SpreadSubsample

Alqaraawi, A., Alwosheel, A., & Alasaad, A. (2016). Heart rate variability estimation in photoplethysmography signals using Bayesian learning approach. *Healthcare Technology Letters*, *3*(2), 136-142. https://doi.org/10.1049/htl.2016.0006

Alzoubi, O., Fossati, D., D'Mello, S., & Calvo, R. A. (2013). Affect detection and classification from the non-stationary physiological data. *Proceedings - 2013 12th International Conference on Machine Learning and Applications, ICMLA 2013*, *1*, 240-245. https://doi.org/10.1109/ICMLA.2013.49

Ambulatory Monitoring, I. (n.d.). AMI: Physiological Actigraph monitoring of ambulatory subjects for sleep, psychiatric and movement disorders. Retrieved July 1, 2017, from http://www.ambulatory-monitoring.com/micro_sensors.html

Ancoli-Israel, S., Cole, R., Alessi, C., Chambers, M., Moorcroft, W., & Pollak, C. P. (2003). The role of actigraphy in the study of sleep and circadian rhythms. *Sleep*, *26*(3), 342-392.

Andale. (2012). Pearson Correlation: Definition and Easy Steps for Use. Retrieved October 28, 2017, from http://www.statisticshowto.com/what-is-the-pearson-correlation-coefficient/

Angel, M. F., & Bonarini, A. (2014). Studying People ' s Emotional Responses to Robot ' s Movements in a Small Scene.

Antonucci, T. C. (2001). Social relations: an examination of social networks, social support, and sense of control. *Handbook of the Psychology of Aging*, (November), 427-453.

Applied Science Laboratories (2006). Applied Science Laboratories Model 504 Eye Tracker and Gaze Tracker System Setup and Operations Manual. *Science*, (October), 1-55.

Aracena, C., Basterrech, S., Snael, V., & Velasquez, J. (2016). Neural Networks for Emotion Recognition Based on Eye Tracking Data. *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015.* https://doi.org/10.1109/SMC.2015.460

Arduino.(2018). ARDUINO. Retrieved from https://www.arduino.cc/

Armon, C. (2016). Polysomnography: Overview, Parameters Monitored, Procedures. Retrieved July 1, 2017, from http://emedicine.medscape.com/article/1188764-overview

Arnold, M. B. (1970). Perennial problems in the field of emotion. In *Feelings and emotions : The Loyola Symposium* (Vol. 7, pp. 169-185).

Aschoff, J. (1983). Circadian control of body temperature. *Journal of Thermal Biology*, *8*(1-2), 143-147. https://doi.org/10.1016/0306-4565(83)90094-3

Attanasio, V., Andrasik, F., Blanchard, E. B., & Arena, J. G. (1984). Psychometric properties of the SUNYA revision of the psychosomatic symptom checklist. *Journal of Behavioral Medicine*, *7*(2), 247-257. https://doi.org/10.1007/BF00845390

Ax, A. F. (1953). The physiological differentiation between fear and anger in humans. *Psychosomatic Medicine*, *15*(5), 433-442. https://doi.org/10.1097/00006842-195309000-00007

Babiker, A., Faye, I., & Malik, A. (2013). Pupillary behavior in positive and negative emotions.

IEEE ICSIPA 2013 - IEEE International Conference on Signal and Image Processing Applications, 7-11. https://doi.org/10.1109/ICSIPA.2013.6708037

Backs, R. W., Navidzadeh, H. T., & Xu, X. (2000). Cardiorespiratory indices of mental workload during simulated air traffic control. *Proceedings of the IEA 2000/HFES 2000 Congress*, *3*(13), 89-92. https://doi.org/10.1177/154193120004401323

Bagby, M., Parker, J. D. a, & Taylor, G. J. (1994). the Twenty-Item Item Selection Toronto and Cross-Validation Structure. *Journal of Psychosomatic Research*, *38*(1), 23-32. https://doi.org/10.1016/0022-3999(94)90005-1

Bago d'Uva, T., Van Doorslaer, E., Lindeboom, M., & O'Donnell, O. (2008). Does reporting heterogeneity bias the measurement of health disparities? *Health Economics*, *17*(3), 351-375. https://doi.org/10.1002/hec.1269

Bakhtiyari, K., & Husain, H. (2014). Fuzzy Model on Human Emotions Recognition. *ArXiv Preprint ArXiv:1407.1474*, 77-82. https://doi.org/10.13140/2.1.1595.8081

Barea, R., Boquete, L., Rodriguez-Ascariz, J. M., Ortega, S., & López, E. (2011). Sensory system for implementing a human-computer interface based on electrooculography. *Sensors*, *11*(1), 310-328. https://doi.org/10.3390/s110100310

Basu, S., Bag, A., Mahadevappa, M., Mukherjee, J., & Guha, R. (2016). Affect detection in normal groups with the help of biological markers. *12th IEEE International Conference Electronics, Energy, Environment, Communication, Computer, Control: (E3-C3), INDICON 2015,* 1-6. https://doi.org/10.1109/INDICON.2015.7443733

Batson, C. D., Shaw, L. L., & Oleson, K. C. (1992). Differentiating affect, mood, and emotion: Toward functionally based conceptual distinctions. *Emotion*, *13*, 294-326.

Battaglia, M., Ogliari, A., Zanoni, A., Citterio, A., Pozzoli, U., Giorda, R., ... Marino, C. (2005). Influence of the serotonin transporter promoter gene and shyness on children's cerebral responses to facial expressions. *Archives of General Psychiatry*, *62*(1), 85-94. https://doi.org/10.1001/archpsyc.62.1.85

Bauer, G., & Lukowicz, P. (2012). Can smartphones detect stress-related changes in the behavior of individuals? *2012 IEEE International Conference on Pervasive Computing and Communications Workshops, PERCOM Workshops 2012*, (March), 423-426. https://doi.org/10.1109/PerComW.2012.6197525

Baumeister, R. F., Campbell, J. D., Krueger, J. I., Vohs, K. D., Solomon, L. J., Rothblum, E. D., ... Fend, H. a. (2013). Mindfulness and Self-esteem: A Systematic Review. *Personality and Individual Differences*, *35*(2), 213-240. https://doi.org/10.1007/s12671-015-0407-6

Beck,A.T.;Steer,R.A,Brown, G. . (1996). Beck Depression Inventory-Second Edition (BDI-II) | National Child Traumatic Stress Network - Child Trauma Home. Retrieved June 18, 2017, from http://www.nctsnet.org/content/beck-depression-inventory-second-edition

Beedie, C. J., Terry, P. C., & Lane, A. M. (2005). Distinctions between emotion and mood. *Cognition and Emotion.* https://doi.org/10.1080/02699930541000057

Bellman, R. E. (1961). Adaptive control processes: A guided tour. *Princeton University Press*, *28*, 1-19. Retrieved from http://arxiv.org/abs/1302.6677

Biondi, M., & Picardi, A. (1999). Psychological stress and neuroendocrine function in humans: the last two decades of research. *Psychotherapy and Psychosomatics*, *68*(3), 114-150. https://doi.org/12323

Biopac Systems (2017). Cardiac Output Estimate from BP. Retrieved April 20, 2017, from https://www.biopac.com/?app-advanced-feature=cardiac-output-estimate-from-bp

Biopac Systems Inc (2017a). Data Acquisition, Loggers, Amplifiers, Transducers, Electrodes | BIOPAC. Retrieved June 17, 2017, from https://www.biopac.com/

Biopac Systems Inc (2017b). ECG: Cardiology | RMSSD for HRV Analysis | Research | BIOPAC. Retrieved April 17, 2017, from https://www.biopac.com/application/ecg-cardiology/advanced-feature/rmssd-for-hrv-analysis/

Biopac Systems Inc. (2017c). MP System Comparison: MP150 vs. MP100 | BIOPAC. Retrieved June 17, 2017, from https://www.biopac.com/knowledge-base/mp-system-comparison-mp150-vs-mp100/

Biopac Systems Inc. (2017d). Noninvasive Blood Pressure Amplifier - NIBP100D.

Biopac Systems Inc. (2017e). Upgrade to MP160 with AcqKnowledge Windows | MP160U-W, MP160U-M | Research | BIOPAC. Retrieved June 17, 2017, from https://www.biopac.com/product/mp100-system-upgrades/

Biosemi (n.d.). Analog Input Box, AIB. Retrieved June 16, 2017, from https://www.biosemi.com/aib.htm

Birdwhistell, R. L. (1970). *Kinesics and Context: Essays on Body-motion Communication*. *Kinesics and Context: Essays on Body-motion Communication*. University of Pennsylvania press. Retrieved from https://books.google.com/books?id=NvzCSAAACAAJ&pgis=1

Blascovich, J., & Tomaka, J. (1996). The Biopsychosocial Model of Arousal Regulation. In *Advances in Experimental Social Psychology* (Vol. 28, pp. 1-51). https://doi.org/10.1016/S0065-2601(08)60235-X

Blood, N. N., & Monitoring, P. (2017). Product sheet, 1-3.

Bogomolov, A., Lepri, B., & Pianesi, F. (2013). Happiness recognition from mobile phone data. *Proceedings - SocialCom/PASSAT/BigData/EconCom/BioMedCom 2013*, 790-795. https://doi.org/10.1109/SocialCom.2013.118

Bogomolov, A., Trento, I.-P., Lepri, B., Pianesi, F., Kessler, F. B., Kessler, F. B., & Pentland, A. S. (2014). Daily Stress Recognition from Mobile Phone Data , Weather Conditions and Individual Traits, 477-486. https://doi.org/10.1145/2647868.2654933

Bonatti, L. (2006). Psyscope X. Retrieved June 2, 2017, from http://psy.ck.sissa.it/

Bonnemeier, H., Richardt, G., Potratz, J., Wiegand, U. K. H., Brandes, A., Kluge, N., & Katus, H. A. (2003). Circadian profile of cardiac autonomic nervous modulation in healthy subjects: differing effects of aging and gender on heart rate variability. *Journal of Cardiovascular Electrophysiology*, *14*(8), 791-799. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12890036

Bos, D. (2010). EEG-based Emotion Recognition. *IEEE Transactions on Biomedical Engineering*, *57*(7), 1798-1806. https://doi.org/10.1109/TBME.2010.2048568

Boucsein, W. (2012). Electrodermal Activity. Electrodermal *Activity*, *3*(1973), 3-67. https://doi.org/10.1007/978-1-4614-1126-0

Boudreau, P., Dumont, G., Kin, N. M. K. N. Y., Walker, C. D., & Boivin, D. B. (2011). Correlation of heart rate variability and circadian markers in humans. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 681-684. https://doi.org/10.1109/IEMBS.2011.6090153

Bound, J. (1991). Self-Reported vs. Objective Measures of Health in Retirement Models. *The Journal of Human Resources*, *26*(1), 106-138. https://doi.org/10.3386/w2997

Boyle, G. J. (1984). Reliability and validity of Izard ' s Differential Emotions Scale undergraduates under each of four imaginal mood-induction conditions (labelled : General Depression ,. *Depression*, *5*(6), 747-750.

Bracewell, R. N. (2014). The Fourier Transform. *Diagnostic Ultrasound Imaging: Inside Out*, *260*(6), 765-783. https://doi.org/10.1016/B978-0-12-396487-8.00029-X

Bradley, M.M., & Lang, P. J. (1999). International affective digitized sounds (IADS): Stimuli, instruction manual and affective ratings. *Technical Report B-2*.

Bradley, Margaret M., & Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry*, *25*(1), 49-59. https://doi.org/10.1016/0005-7916(94)90063-9

Bradley, Margaret M., Miccoli, L., Escrig, M. A., & Lang, P. J. (2008). The pupil as a measure of emotional arousal and autonomic activation. *Psychophysiology*, *45*(4), 602-607. https://doi.org/10.1111/j.1469-8986.2008.00654.x

Bradley, P. C., & Holloway, R. (n.d.). W-BQ12 (English for Portugal), *3*, 96.

Brainquiry (n.d.). PET 4.0 - 4 channels EEG with active electrodes. Brainquiry*.com*.

Brainquiry.(2017). BioExplorer Software License - brainquiry - Wireless, high quality signal EEG, EMG, ECG. Retrieved July 15, 2017, from http://www.brainquiry.com/bioexplorer-software-license/

Brandão, R. M. (n.d.). Basic Concepts in Statistics.

Branquiry (2017). brainquiry - Wireless, high quality signal EEG, EMG, ECG. Retrieved July 15, 2017, from http://www.brainquiry.com/

Briggs, M. I. (2015). MBTI - Careers For Your Personality. *PhD Proposal*, *1.* https://doi.org/10.1017/CBO9781107415324.004

Brugha, T., Bebbington, P., Tennant, C., & Hurry, J. (1985). The List of Threatening Experiences: a subset of 12 life event categories with considerable long-term contextual threat. *Psychological Medicine*, *15*(01), 189. https://doi.org/10.1017/S003329170002105X

Brugha, T. S., & Cragg, D. (1990). The List of Threatening Experiences: the reliability and validity of a brief life events questionnaire. *Acta Psychiatrica Scandinavica*, *82*(1), 77-81. https://doi.org/10.1111/j.1600-0447.1990.tb01360.x

Buchanan, T. W., & Lovallo, W. R. (2001). Enhanced memory for emotional material following stress-level cortisol treatment in humans. *Psychoneuroendocrinology*, *26*(3), 307-317. https://doi.org/10.1016/S0306-4530(00)00058-5

Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys (CSUR)*, *1*(June), 1-33. https://doi.org/http://dx.doi.org/10.1145/2499621

Burnett, S., Bird, G., Moll, J., Frith, C., & Blakemore, S. J. (2009). Development during Adolescence of the Neural Processing of Social Emotion. *Journal of Cognitive Neuroscience*, *21*(9), 1736-1750. https://doi.org/10.1162/jocn.2009.21121.Development

Business Wire (2007). Cisbio Bioassays and Orion Diagnostica Oy Sign an Agreement for Steroid Radioimmunoassays | Business Wire. Retrieved June 11, 2017, from http://www.businesswire.com/news/home/20131007006186/en/Cisbio-Bioassays-Orion-Diagnostica-Oy-Sign-Agreement

Busso, C., Deng, Z., Yildirim, S., Bulut, M., Lee, C. M., Kazemzadeh, A., ... Narayanan, S. (2004). Analysis of emotion recognition using facial expressions, speech and multimodal information. *Proceedings of the 6th International Conference on Multimodal Interfaces - ICMI '04*, 205. https://doi.org/10.1145/1027933.1027968

Buutcher, N. N., Graham, J. R., Ben-Porath, Y. S., Tellegen, Y. S., Dahlstrom, W. G., & Kaemmer, B. (2001). *Minnesota Multiphasic Personality Inventory-2*. Psychological Corporation. https://doi.org/10.1002/9781119311263.app1

Buysse, D. J., Reynolds, rd C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. *Psychiatry Research.* https://doi.org/10.1016/0165-1781(89)90047-4

Č, J. Š, Škoda, J., Krbal, M., & Wasserbauer, V. Č. (2016). Comparison of Light Sources for Household Use due Circadian Effect, *1*, 2-5.

Caballe, S. (2015). Towards a Multi-modal Emotion-Awareness e-Learning System. *Proceedings - 2015 International Conference on Intelligent Networking and Collaborative Systems, IEEE INCoS 2015*, 280-287. https://doi.org/10.1109/INCoS.2015.88

Cacioppo, J.T., Berntson, G.G., Larsen, J.T., Poehlmann, K.M., Ito, T. A. (2000). *Cacioppo, JT - The psychophysiology of emotion*. *The psychophysiology of emotion.* New York, USA: The Guilford Press.

Cahn, J. E. (1990). Generating Expression in Synthesized Speech, 177.

Cajochen, C., Zeitzer, J. M., Czeisler, C. a, & Dijk, D. J. (1999). Dose-response relationship for light intensity and alertness and its ocular and EEG correlates. *Behavioural Brain Research*, *115*, 75-83.

Calvert, C. A. (1998). Heart rate variability. *Vet Clin North Am Small Anim Pract*, *28*(6), 1409-1427, viii. https://doi.org/10.1016/B978-0-444-53491-0.00031-6

Cambridge University. (2008). Feature selection Chi2 Feature selection. Retrieved October 29, 2017, from https://nlp.stanford.edu/IR-book/html/htmledition/feature-selectionchi2-feature-selection-1.html

Camurri, A., Mazzarino, B., & Volpe, G. (2004). Analysis of expressive gesture: The eyesweb expressive gesture processing library. *In Gesture-Based Communication in Human-Computer Interaction, LNAI 2915*, 460-467. https://doi.org/10.1007/978-3-540-24598-8_42

Canini, L., Benini, S., Migliorati, P., & Leonardi, R. (2009). Emotional identity of movies. *Proceedings - International Conference on Image Processing, ICIP*, 1821-1824. https://doi.org/10.1109/ICIP.2009.5413556

Canli, T., Desmond, J. E., Zhao, Z., Glover, G., & Gabrieli, J. D. E. (1998). Hemispheric asymmetry for emotional stimuli detected with fMRI. *Neuroreport*, *9*(14), 3233-3239.

Capineri, L. (2014). Resistive sensors with smart textiles for wearable technology: From fabrication processes to integration with electronics. *Procedia Engineering*, *87*, 724-727. https://doi.org/10.1016/j.proeng.2014.11.748

Castellano, G., Villalba, S. D., & Camurri, A. (2007). Recognising Human Emotions from Body Movement and Gesture Dynamics. *Affective Computing and Intelligent Interaction*, 71-82. https://doi.org/10.1007/978-3-540-74889-2_7

Chan, G. S. H., Middleton, P. M., Lovell, N. H., & Celler, B. G. (2005). Extraction of photoplethysmographic waveform variability by lowpass filtering. *Proceedings of the 2005 IEEE*, *c*, 5568-5571.

Chan, M., Estève, D., Fourniols, J.-Y., Escriba, C., & Campo, E. (2012). Smart wearable systems: Current status and future challenges. *Artif Intell Med*, *56*(3), 137-156. https://doi.org/http://dx.doi.org/10.1016/j.artmed.2012.09.003

Chandler, C., & Cornes, R. (2012). Biometric Measurement of Human Emotions, *4*(2).

Chanel, G. (2009). Emotion assessment for affective computing based on brain and peripheral signals. *PhD Thesis*, 194. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.155.4044&rep=rep1&type=pdf

Chang, C.-Y., Lin, Y.-M., & Zheng, J.-Y. (2012). Physiological Angry Emotion Detection Using Support Vector Regression. *2012 15th International Conference on Network-Based Information Systems*, 592-596. https://doi.org/10.1109/NBiS.2012.78

Chang, C.-Y., Zheng, J.-Y., & Wang, C.-J. (2010). Based on Support Vector Regression for emotion recognition using physiological signals. *The 2010 International Joint Conference on Neural Networks (IJCNN)*, (April 2015), 1-7. https://doi.org/10.1109/IJCNN.2010.5596878

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, *16*, 321-357. https://doi.org/10.1613/jair.953

Cheever, N. A., Rosen, L. D., Carrier, L. M., & Chavez, A. (2014). Out of sight is not out of mind: The impact of restricting wireless mobile device use on anxiety levels among low, moderate and high users. *Computers in Human Behavior*, *37*, 290-297. https://doi.org/10.1016/j.chb.2014.05.002

Chellappa, S. L., Steiner, R., Blattner, P., Oelhafen, P., Götz, T., & Cajochen, C. (2011). Non-Visual Effects of Light on Melatonin, Alertness and Cognitive Performance: Can Blue-Enriched Light Keep Us Alert? *PLoS ONE*, *6*(1), e16429. https://doi.org/10.1371/journal.pone.0016429

Chen, D., & Vertegaal, R. (2004). Using mental load for managing interruptions in physiologically attentive user interfaces. *Extended Abstracts of the 2004 Conference on Human Factors and Computing Systems - CHI '04*, (January 2004), 1513. https://doi.org/10.1145/985921.986103

Chen, L. S., Huang, T. S., Miyasato, T., & Nakatsu, R. (1998). Multimodal Human Emotion Expression Recognition. *Third International Conf Automatic Face and Gesture Recognition*, *13*(7), 366-371. https://doi.org/10.1109/AFGR.1998.670976

Chen, W., Jaques, N., Taylor, S., Sano, A., Fedor, S., & Picard, R. W. (2014). WAVELET-BASED MOTION ARTIFACT REMOVAL FOR ELECTRODERMAL ACTIVITY Electrodermal Activity Motion Artifact in EDA Our Method A . Stationary wavelet transform C . Inverse wavelet transform ● EDA data containing motion artifacts was obtained from a.

Chen, Z., Lin, M., Chen, F., Lane, N., Cardone, G., Wang, R., ... Cambell, A. (2013). Unobtrusive Sleep Monitoring using Smartphones. *Proceedings of the ICTs for Improving Patients Rehabilitation Research Techniques.* https://doi.org/10.4108/icst.pervasivehealth.2013.252148

Chittaranjan, G., Jan, B., & Gatica-Perez, D. (2011). Who's who with big-five: Analyzing and classifying personality traits with smartphones. *Proceedings - International Symposium on Wearable Computers, ISWC*, 29-36. https://doi.org/10.1109/ISWC.2011.29

Choppin, A. (2000). EEG-Based Human Interface for Disabled Individuals : Emotion Expression with Neural Networks Submitted for the Master Degree. *Emotion*.

Christie, M. J. (1981). Electrodermal activity in the 1980s: a review. *Journal of the Royal Society of Medicine*, *74*(April), 616-622.

Cisbio (2016). Trousse pour le dosage radioimmunologique du cortisol serque et salivaire | Cisbio. Retrieved June 11, 2017, from http://www.cisbio.com/diagnostics/products/endocrinologie/dosage-radioimmunologique-cortisol-serique-salivaire

Class SpreadSubsample (n.d.). Retrieved October 29, 2017, from http://weka.sourceforge.net/doc.stable/weka/filters/supervised/instance/SpreadSubsample.html

Coburn, K. L., & Moreno, M. a. (1988). Facts and artifacts in brain electrical activity mapping. *Brain Topography*, *1*(1), 37-45. https://doi.org/10.1007/BF01129338

Cohen, J., MacWhinney, B., Flatt, M., & Provost, J. (1993). PsyScope: An interactive graphic system for designing and controlling experiments in the psychology laboratory using Macintosh computers. *Behavior Research Methods, Instruments, & Computers*, 25(2), 257-271. https://doi.org/10.3758/BF03204507

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A Global Measure of Perceived Stress. *Journal of Health and Social Behavior.* https://doi.org/10.2307/2136404

Cohen, S, & Wills, T. A. (1985). Stress, social support, and the buffering hyothesis. *Psychological Bulletin*, *98*(2), 310-357. https://doi.org/10.1037/0033-2909.98.2.310

Cohen, Sheldon, & Herbert, T. B. (1996). HEALTH PSYCHOLOGY: Psychological Factors and Physical Disease from the Perspective of Human Psychoneuroimmunology. *Annu. Rev. Psychol*, *47*(1993), 113-142. https://doi.org/doi:10.1146/annurev.psych.47.1.113

Cole, R. J., Kripke, D. F., Gruen, W., Mullaney, D. J., & Gillin, J. C. (1992). Automatic sleep/wake identification from wrist activity. *Sleep*, *15*(5), 461-469. https://doi.org/10.1093/sleep/15.5.461

Cootes, T. F., Taylor, C. J., Cooper, D. H., & Graham, J. (1995). Active Shape Models-Their Training and Application. *Computer Vision and Image Understanding*, *61*(1), 38-59. https://doi.org/10.1006/cviu.1995.1004

Cornelissen, J., & Waterman, H. I. (2016). Advanced Biosignal Acquisition, Proecssing and Analysis - Product Catalogue.

Cowie, R., Douglas-Cowie, E., Savvidou, S., Mcmahon, E., Sawey, M., & Schröder, M. (2000). "Feeltrace: An instrument for recording perceived emotion in real time. *ISCA Workshop on Speech {&} Emotion*, 19-24. https://doi.org/citeulike-article-id:3721917

Cristinacce, D., & Cootes, T. (2008). Automatic feature localisation with constrained local models. *Pattern Recognition*, *41*(10), 3054-3067. https://doi.org/10.1016/j.patcog.2008.01.024

Cronbach, L. (1951). Coefficient alpha and the internal structure of tests, Psychometrika. *Psychometrika*, *16*(3), 297-334.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297-334. https://doi.org/10.1007/BF02310555

Crossman, A. (2017). Correlation Analysis in Sociological Research. Retrieved October 29, 2017, from https://www.thoughtco.com/what-is-correlation-analysis-3026696

Crowne, D P, & Marlowe, D. (1960). Marlowe-Crowne Social Desirability Scale. *Journal of Consulting Psychology*, *24*(4), 349-354. https://doi.org/10.1037/h0047358

Crowne, Douglas P., & Marlowe, D. (1960). A new scale of social desirability independent of psychopathology. *Journal of Consulting Psychology*, *24*(4), 349-354. https://doi.org/10.1037/h0047358

Cruz, A., Garcia, D., Pires, G., & Nunes, U. (2015). Facial Expression Recognition based on EOG toward Emotion Detection for Human-Robot Interaction. *Biosignals*, *2*, 31-37. Retrieved from http://www.dblp.org/rec/bibtex/conf/biostec/CruzGPN15%5Cnpapers2://publication/uuid/F0A7D9E6-D8E8-4967-B20B-7EE34D518E7D

Cryptography, P. (2009). Mel Frequency Cepstral Coefficient (MFCC) tutorial. Retrieved March 13, 2017, from http://practicalcryptography.com/miscellaneous/machine-learning/guide-mel-frequency-cepstral-coefficients-mfccs/

Csail, M. I. T. (n.d.). The AdaBoost algorithm, (0), 17.

Curcio, G., Piccardi, L., Ferlazzo, F., Giannini, A. M., Burattini, C., & Bisegna, F. (2016). LED lighting effect on sleep, sleepiness, mood and vigor. *EEEIC 2016 - International Conference on Environment and Electrical Engineering*, 0-4. https://doi.org/10.1109/EEEIC.2016.7555791

Czeisler, C. A., Allan, J. S., Strogatz, S. H., Ronda, J. M., Sanchez, R., Rios, C. D., ... Kronauer, R. E. (1986). Bright light resets the human circadian pacemaker independent of the timing of the sleep-wake cycle. *Science*, *233*(4764), 667-671. https://doi.org/10.1126/science.3726555

DeGiorgio, C. M., Miller, P., Meymandi, S., Chin, A., Epps, J., Gordon, S., ... Harper, R. M. (2010). RMSSD, a measure of vagus-mediated heart rate variability, is associated with risk factors for SUDEP: The SUDEP-7 Inventory. *Epilepsy and Behavior*, *19*(1), 78-81. https://doi.org/10.1016/j.yebeh.2010.06.011

Dellaert, F., Polzin, T., & Waibel, A. (1973). Recognizing emotion in speech. *Proceeding of Fourth International Conference on Spoken Language Processing. ICSLP '96*, *3*, 1970-1973. https://doi.org/10.1109/ICSLP.1996.608022

Denissen, J. J. a, Butalid, L., Penke, L., & van Aken, M. a G. (2008). The effects of weather on daily mood: a multilevel approach. *Emotion (Washington, D.C.)*, *8*(5), 662-667. https://doi.org/10.1037/a0013497

Desmet, P. (2003). Measuring Emotion: Development and Application of an Instrument to Measure Emotional Responses to Products (pp. 111-123). Springer Netherlands.

https://doi.org/10.1007/1-4020-2967-5_12

Desmet, P. M. a. (2005). Measuring Emotion: Development and Application of an Instrument to Measure Emotional Responses to Products. *Funology: From Usability to Enjoyment*, *3*, 111-124. https://doi.org/10.1007/1-4020-2967-5

Dhall, A., Asthana, A., Goecke, R., & Gedeon, T. (2011). Emotion recognition using PHOG and LPQ features. *2011 IEEE International Conference on Automatic Face and Gesture Recognition and Workshops, FG 2011*, 878-883. https://doi.org/10.1109/FG.2011.5771366

Dickerson, S. S., & Kemeny, M. E. (2004). Acute stressors and cortisol responses: a theoretical integration and synthesis of laboratory research. *Psychological Bulletin*, *130*(3), 355-391. https://doi.org/10.1037/0033-2909.130.3.355

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment.* https://doi.org/10.1207/s15327752jpa4901_13

Dienstbier, R. A. (1989). Arousal and physiological toughness: implications for mental and physical health. *Psychological Review*, *96*(1), 84-100. https://doi.org/10.1037/0033-295X.96.1.84

Dimensional Imaging LTD. (2017). DI3D System - 3D Facial Image Capture. Retrieved July 1, 2017, from http://www.di4d.com/systems/di3d-system/

Ding, X., Boney-montoya, J., Owen, B. M., Bookout, A. L., Coate, C., Mangelsdorf, D. J., & Kliewer, S. a. (2013). BKlotho is required for fibroblast growth factor 21 effects on growth and metabolism. *Cell Metabolism*, *16*(3), 387-393. https://doi.org/10.1016/j.cmet.2012.08.002.

Dishman, R. K., Nakamura, Y., Garcia, M. E., Thompson, R. W., Dunn, a L., & Blair, S. N. (2000). Heart rate variability, trait anxiety, and percieved stress among physically fit men and women. *International Journal of Psychophysiology*, *37*, 121-133.

Ditor, D. S., Macdonald, M. J., Kamath, M. V, Bugaresti, J., Adams, M., McCartney, N., & Hicks, a L. (2005). Kubios HRV - Heart rate variability analysis software. https://doi.org/10.1016/j.cmpb.2013.07.024

Dong, W., Lepri, B., & Pentland, A. (2011). Modeling the co-evolution of behaviors and social relationships using mobile phone data. *Proceedings of the 10th International Conference on Mobile and Ubiquitous Multimedia - MUM '11*, 134-143. https://doi.org/10.1145/2107596.2107613

Duda, R. O., Hart, P. E., & Stork, D. G. (2001). Pattern Classification. *New York: John Wiley, Section. https://doi.*org/10.1007/BF01237942

Dunbar, M., Ford, G., & Hunt, K. (1998). Why is the receipt of social support associated with increased psychological distress? An examination of three hypotheses. *Psychology and Health*, *13*(3), 37-41. https://doi.org/10.1080/08870449808407308

Dunst & Trivette, C. M., C. L. (1990). Assessment of social support in early intervention programs. *Handbook of Early Childhood Intervention*, 326-349.

Eagle, N., & Pentland, A. (2006). Reality mining: Sensing complex social systems. *Personal and Ubiquitous Computing*, *10*(4), 255-268. https://doi.org/10.1007/s00779-005-0046-3

Eckert, M., Gil, A., Zapatero, D., Meneses, J., & Mart??nez Ortega, J. F. (2016). Fast facial expression recognition for emotion awareness disposal. *IEEE International Conference on Consumer Electronics - Berlin, ICCE-Berlin*, *2016-Octob,* 179-183. https://doi.org/10.1109/ICCE-Berlin.2016.7684749

Ehrampoosh, A., Yousefi-koma, A., & Mohtasebi, S. (2016). EMG-Based Estimation of Shoulder Kinematic Using Neural Network and Quadratic Discriminant Analysis, 471-476.

Ekman, Paul; Freiesen, W. V. (2003). *Unmasking The Face: A guide to recognizing emotions from facial expressions*. Malor Books.

Ekman, Paul; Friesen, W. (1978). Facial Action Coding System: A Technique for the Measurement of Facial Movement. Palo Alto: Consulting Psychologists Press.

Ekman, P. (1989). The argument and evidence about universals in facial expressions of emotion. *Handbook of Social Psychophysiology*. Retrieved from https://www.paulekman.com/wp-content/uploads/2013/07/The-Argument-And-Evidence-About-Universals-In-FacialExpressi.pdf

Electrophysiology, T. F. o. t. E. S. o. C. t. N. A. S. (1996a). Heart Rate Variability : Standards of Measurement, Physiological Interpretation, and Clinical Use. *Circulation*, *93*(5), 1043-1065. https://doi.org/10.1161/01.CIR.93.5.1043

Electrophysiology, T. F. o. t. E. S. o. C. t. N. A. S. (1996b). Heart Rate Variability : Standards of Measurement, Physiological Interpretation, and Clinical Use. *Circulation*, *93*(5), 1043-1065. https://doi.org/10.1161/01.CIR.93.5.1043

Ellenbogen, M. a, Schwartzman, A. E., Stewart, J., & Walker, C.-D. C.-D. (2002). Stress and selective attention : The interplay of mood,cortisol levels, and emotional information processing. *Psychophysiology*, *39*(6), 723-732. https://doi.org/10.1017/S0048577202010739

Emotiv. (2017). EMOTIV SDK and Apps for Developers and proprietary research. Retrieved July 15, 2017, from https://www.emotiv.com/developer/

Empatica Inc. (2017). Embrace Seizure Detection | Manage Epilepsy | SUDEP. Retrieved June 24, 2018, from https://www.empatica.com/embrace/

ERIKG Group (2011). ERIKG Group - Grass Technologies Full Sleep Study Solutions Provider. Retrieved from http://www.erikg.com/grass.html

Estrada, E., Nazeran, H., Barragan, J., Burk, J. R., Lucas, E. A., & Behbehani, K. (2006). EOG and EMG: Two important switches in automatic sleep stage classification. *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, 2458-2461. https://doi.org/10.1109/IEMBS.2006.260075

Expert tools for Heart Rate analysis. (2016). CardioMood.

Fasel, B., & Luettin, J. (2003). Automatic facial expression analysis: a survey. *Pattern Recognition*, *36*(1), 259-275. https://doi.org/10.1016/S0031-3203(02)00052-3

Fatourechi, M., Bashashatiemail, A., Wardemail, R. K., & Birchemail, G. E. (2007). EMG and EOG Artifacts in Brain-Computer Interface Systems: A Survey. *Clinical Neurophysiology*, *118*(3), 480-494.

Faust, V., Weidmann, M., & Wehner, W. (1974). The influence of meteorological factors on children and youths: a 10 per cent random selection of 16000 pupils and apprentices of Basle City (Switzerland). *Acta Paedopsychiatrica*, *40*(4), 150-156. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/4597618

Fergus, A. (n.d.). How To Easily Measure Your Heart Rate Variability. Retrieved September 9, 2018, from https://www.alexfergus.com/blog/how-to-easily-measure-your-heart-rate-variability

Finapres Medical Systems BV (2012). Finapres Medical Systems | Products - Finapres® NOVA. Retrieved June 16, 2017, from http://www.finapres.com/Products/Finapres-NOVA

Fiori, K. L., Antonucci, T. C., & Cortina, K. S. (2006). Social Network Typologies and Mental Health among Older Adults. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *61B*(1), 25-32. Retrieved from http://search.proquest.com/docview/61610848?accountid=13374

Fisher, R. A. (1936a). the Use of Multiple Measurements in Taxonomic Problems. *Annals of Eugenics*, *7*(2), 179-188. https://doi.org/10.1111/j.1469-1809.1936.tb02137.x

Fisher, R. A. (1936b). THE USE OF MULTIPLE MEASUREMENTS IN TAXONOMIC PROBLEMS. *Annals of Eugenics*, *7*(2), 179-188. https://doi.org/10.1111/j.1469-1809.1936.tb02137.x

FLIR Systems, I. (n.d.). FLIR Advanced Thermal Solutions: FLIR X6-8000sc Infrared Camera for Research & Science. Retrieved July 1, 2017, from http://www.flir.com/science/display/?id=46802

Source, R. (2015). Taking a serotonin level exam. Retrieved April 9, 2017, from http://www.vladman.net/blog/fazer-um-exame-ao-nivel-de-serotomina

Fortin, J., Mars, W., Gr?llenberger, R., Hacker, A., Habenbacher, W., Heller, A., ... Skrabal, F. (2006). Continuous non-invasive blood pressure monitoring using concentrically interlocking control loops. *Computers in Biology and Medicine*, *36*(9), 941-957. https://doi.org/10.1016/j.compbiomed.2005.04.003

Fraunhofer IIS. (2017). SHORE™ - pioneering facial analysis. Retrieved from https://www.iis.fraunhofer.de/en/ff/bsy/tech/bildanalyse/shore-gesichtsdetektion.html

Frazão, A. (2016a). Understand what Cortisol is and what it is used for. Retrieved April 8, 2017, from https://www.tuasaude.com/cortisol/

Frazão, A. (2016b). Indications and Mode of use of Melatonin. Retrieved April 8, 2017, from https://www.tuasaude.com/melatonina/

Frijda, N. H. (1986). *The Emotions*. Cambridge University Press. Retrieved from https://books.google.pt/books?id=QkNuuVf-pBMC

Fuke, S. (2013). Blood pressure estimation from pulse wave velocity measured on the chest. *Psychophysiology*, *1*(1), 3-6. https://doi.org/10.1109/JSEN.2014.2345779

Fukumto, M., & Nagamatsu, R. (2016). Feedback of Laughter by Detecting Variation in Respiration Amplitude for Augmenting Laughter. *2016 10th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS)*, 139-142. https://doi.org/10.1109/IMIS.2016.122

Fukunaga, K. (1990). *Introduction to Statistical Pattern Recognition*. *Pattern Recognition* (Vol. 22). https://doi.org/10.1016/0098-3004(96)00017-9

Fuller, R. W. (1996). The influence of fluoxetine on aggressive behavior. *Neuropsychopharmacology*, *14*(2), 77-81. https://doi.org/10.1016/0893-133X(95)00110-Y

Fulton, B., & Medlock, M. (2003). Beyond Focus Groups : Getting More Useful Feedback from Consumers. *Game Developers Conference*. San Jose, CA.

g.tec. (2017). g.tec medical engineering. Retrieved July 8, 2017, from http://www.gtec.at/Products/Hardware-and-Accessories/g.MOBIlab-Specs-Features

Gama, J., Carvalho, A., Faceli, K., Lorena, A., & Oliveira, M. (2012). *Extração de Conhecimento de Dados - Data Mining* (2nd ed.). Lisboa: Edições Sílabo, Lda.

Gao, M., Olivier, N. B., & Mukkamala, R. (2016). Comparison of noninvasive pulse transit time estimates as markers of blood pressure using invasive pulse transit time measurements as a reference. *Physiological Reports*, *4*(10), e12768. https://doi.org/10.14814/phy2.12768

Garica-Ceja, E., Osmani, V., & Mayora, O. (2015). Automatic Stress Detection in Working Environments from Smartphones' Accelerometer Data: A First Step. *Biomedical and Health Informatics, IEEE Journal Of*, *(to appear*, 1-8. https://doi.org/10.1109/JBHI.2015.2446195

Geerts, B. F., Aarts, L. P., & Jansen, J. R. (2011). Methods in pharmacology: Measurement of cardiac output. *British Journal of Clinical Pharmacology*, *71*(3), 316-330. https://doi.org/10.1111/j.1365-2125.2010.03798.x

George, L. K., Blazer, D. G., Hughes, D. C., & Fowler, N. (1989). Social support and the outcome of major depression. *The British Journal of Psychiatry*, *154*(4), 478-485. https://doi.org/10.1192/bjp.154.4.478

Giakoumis, D., Vogiannou, A., Kosunen, I., Moustakas, K., Tzovaras, D., & Hassapis, G. (2010). Identifying Psychophysiological Correlates of Boredom and Negative Mood Induced During HCI. *Bio-Inspired Human-Machine Interfaces and Healthcare Applications*, 3-12. https://doi.org/10.5220/0002812600030012

Gil, E. A., Aubert, X. L., & Beersma, D. G. M. (2014). Ambulatory estimation of human circadian phase using models of varying complexity based on non-invasive signal modalities. *Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, *2014*, 2278-2281. https://doi.org/10.1109/EMBC.2014.6944074

Gilad-bachrach, R. (2004). Margin Based Feature Selection - Theory and Algorithms.

Gimeno, F., van der Weele, L. T., Koëter, G. H., de Monchy, J. G., & van Altena, R. (1993). Variability of forced oscillation (Siemens Siregnost FD 5) measurements of total respiratory resistance in patients and healthy subjects. *Annals of Allergy*, *71*(1), 56-60. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8328715

Giri, E. P., Fanany, M. I., & Arymurthy, A. M. (2016). Ischemic Stroke Identification Based on EEG and EOG using 1D Convolutional Neural Network and Batch Normalization, 1-13. Retrieved from http://arxiv.org/abs/1610.01757

GM Instruments (2015). GM Instruments - Rhinomanometer, Acoustic Rhinometer, Rhinospirometer, Audiometer & Pneumotachograph.

Gogia, Y., Singh, E., Mohatta, S., & Sreejith, V. (2016). Multi-modal Affect Detection for Learning Applications. In *2016 IEEE Region 10 Conference (TENCON)* (pp. 3747-3751).

Goldberg, D., Bridges, K., Duncan-Jones, P., & Grayson, D. (1988). Detecting anxiety and depression in general medical settings. *Bmj*, *297*(6653), 897-899.

https://doi.org/10.1136/bmj.297.6653.897

Gorestein, C. (1998). Beck's depression inventory : psychometric properties of the portuguese version, (January).

Gouveia, M. J., & Marques, M. (2009). Portuguese version of the spiritual well-being questionnaire (SWBQ): confirmatory analysis of its factorial structure. *Psicologia, Saúde & Doenças*, *10*(2), 285-293.

Gow, R., Thomson, S., Rieder, M., Van Uum, S., & Koren, G. (2010). An assessment of cortisol analysis in hair and its clinical applications. *Forensic Science International*, *196*(1-3), 32-37. https://doi.org/10.1016/j.forsciint.2009.12.040

Gradisar, M., & Lack, L. (2004). Relationships between the circadian rhythms of finger temperature, core temperature, sleep latency, and subjective sleepiness. *Journal of Biological Rhythms*, *19*(2), 157-163. https://doi.org/10.1177/0748730403261560

Group, T. W. (1998). Development of the World Health Organization WHOQOL-BREF quality of life assessment. The WHOQOL Group. *Psychol Med*, *28*(3), 551-558. https://doi.org/10.5.12

Guillotel, P., Fleureau, J., Orlac, I., & Silveira, F. (2013). On the fly user's emotion capture. *Proceedings - 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, ACII 2013*, 713-714. https://doi.org/10.1109/ACII.2013.128

Guinot Jimeno, F. A., Yuste Bielsa, S., Cuadros Fernández, C., Lorente Rodríguez, A. I., & Mercadé Bellido, M. (2011). Objective and subjective measures for assessing anxiety in paediatric dental patients. *European Journal of Paediatric Dentistry*, *12*(4), 239-244.

Gunes, H., & Piccardi, M. (2007). Bi-modal emotion recognition from expressive face and body gestures. *Journal of Network and Computer Applications*, *30*(4), 1334-1345. https://doi.org/10.1016/j.jnca.2006.09.007

Gutmann, M., Grausberg, P., Kyamakya, K., & Klagenfurt, A. U. (2015). Detecting Human Driver ' s Physiological Stress and Emotions Using Sophisticated One-Person Cockpit Vehicle Simulator, 15-18.

Guyon, I., & Elisseeff, A. (2003). An Introduction to Variable and Feature Selection. *Journal of Machine Learning Research (JMLR)*, *3*(3), 1157-1182. https://doi.org/10.1016/j.aca.2011.07.027

Haag, A., Goronzy, S., Schaich, P., & Williams, J. (2004). Emotion Recognition Using Bio-sensors: First Steps towards an Automatic System. *Affective Dialogue Systems*, *i*, 36-48. https://doi.org/10.1007/978-3-540-24842-2_4

Haddy, F. J., Overbeck, H. W., & Daugherty, R. M. (1968). Peripheral vascular resistance. https://doi.org/10.1146/annurev.me.19.020168.001123

Hammerla, N. Y., Kirkham, R., Andras, P., & Ploetz, T. (2013). On preserving statistical characteristics of accelerometry data using their empirical cumulative distribution. *Proceedings of the 17th Annual International Symposium on International Symposium on Wearable Computers - ISWC '13*, 65. https://doi.org/10.1145/2493988.2494353

Harb, F., Hidalgo, M. P., & Martau, B. (2014). Lack of exposure to natural light in the workspace is associated with physiological, sleep and depressive symptoms. *Chronobiology International*, *1*(1), 1-8. https://doi.org/10.3109/07420528.2014.982757

Hardt, J., & Gerbershagen, H. U. (1999). No changes in mood with the seasons: observations in 3000 chronic pain patients. *Acta Psychiatrica Scandinavica*, *100*(4), 288-294. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10510698

Hareli, Shlomo; Parkinson, B. (2017). *What's Social About Social Emotions?*

Haritaoglu, I., Cozzi, A., Koons, D., Flickner, M., Zotkin, D., & Yacoob, Y. (2001). ATTENTIVE TOYS IBM Almaden Research , San Jose , AC 95120 , USA Computer Vision Laboratory University of Maryland , College Park , MD 20742 , USA.

Harmer, C J, Bhagwagar, Z., Perrett, D. I., Völlm, B. A., Cowen, P. J., & Goodwin, G. M. (2003). Acute SSRI administration affects the processing of social cues in healthy volunteers. *Neuropsychopharmacology : Official Publication of the American College of Neuropsychopharmacology*, *28*(1), 148-152. https://doi.org/10.1038/sj.npp.1300004

Harmer, Catherine J., Shelley, N. C., Cowen, P. J., & Goodwin, G. M. (2004). Increased positive versus negative affective perception and memory in healthy volunteers following selective serotonin and norepinephrine reuptake inhibition. *American Journal of Psychiatry*, *161*(7), 1256-1263. https://doi.org/10.1176/appi.ajp.161.7.1256

Harsono, B. (2012). Rancang Bangun Alat Pemantau Detak Jantung Saat Latihan Fisik. *Jurnal Teknik Dan Ilmu Komputer*, *1*(4), 338-346.

Hawkley, L. C., & Cacioppo, J. T. (2010). Loneliness Matters: A Theoretical and Empirical Review of Consequences and Mechanisms. *Annals of Behavioral Medicine*, *40*(2), 218-227. https://doi.org/10.1007/s12160-010-9210-8

Healey, J. A., & Picard, R. W. (2005). Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on Intelligent Transportation Systems*, *6*(2), 156-166. https://doi.org/10.1109/TITS.2005.848368

Healey, J., & Picard, R. (1998). Digital processing of affective signals. *Proceedings of the 1998 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP '98 (Cat. No.98CH36181)*, *6*, 3749-3752. https://doi.org/10.1109/ICASSP.1998.679699

Healey, Jennifer a, Picard, R. W., & Smith, A. C. (2000). Wearable and Automotive Systems for A ect Recognition from Physiology Accepted by Wearable and Automotive Systems for A ect Recognition by, 158.

Heimann, H., Bobon-Schrod, H., Schmocker, A. M., & Bobon, D. P. (1975). Self-rating of mood using a list of adjectives, Zersen's Befindlichkeits-Skala (BS). *L'Encéphale*, *1*(2), 165-183. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1175501

Heitzmann, C. A., & Kaplan, R. M. (1988). Assessment of methods for measuring social support. *Health Psychology*, *7*(1), 75-109. https://doi.org/10.1037//0278-6133.7.1.75

Helander, M. (1978). Applicability of drivers' electrodermal response to the design of the traffic environment. *Journal of Applied Psychology*, *63*(4), 481.

Hendriks, A. A. J., Ormel, J., & van de Willige, G. (1990). Long-term difficulties measured by a self-report questionnaire and semi-structured interview: a comparison of methods [in Dutch]. *Gedrag En Gezondheid*, *18*, 273-283.

Herbon, A., Peter, C., Markert, L., & Meer, E. Van Der. (2005). Emotion studies in HCI - a new approach. *Proceedings of the 2005 HCI International Conference*, (1986). Retrieved from http://www.prometei.de/fileadmin/prometei.de/publikationen/Herbon_etal_2005.pdf

Hermida, R. C., Halberg, F., & Chavarria, F. (1988). Numerical resampling supports melatonin as a potential marker of breast cancer risk. In *IEEE/Engineering in Medicine and Biology Society Annual Conference* (Vol. 10 pt 3, pp. 1088-1089 vol.3). IEEE. https://doi.org/10.1109/IEMBS.1988.94720

Hernandez, J., Morris, R. R., & Picard, R. W. (2011). Call Center Stress Recognition with Person-Specific Models. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6974 LNCS*(PART 1), 125-134.

Hess, E. H., & Polt, J. M. (1960). Pupil size as related to interest value of visual stimuli. *Science (New York, N.Y.)*, *132*(3423), 349-350. https://doi.org/10.1126/science.132.3423.349

Hey, S., Gharbi, A., Von Haaren, B., Walter, K., König, N., & Löffler, S. (2009). Continuous noninvasive pulse transit time measurement for psychophysiological stress monitoring. *Proceedings - International Conference on EHealth, Telemedicine, and Social Medicine, ETELEMED 2009*, 113-116. https://doi.org/10.1109/eTELEMED.2009.35

Hills, P., & Argyle, M. (2002). The Oxford Happiness Questionnaire: A compact scale for the measurement of psychological well-being. *Personality and Individual Differences*, *33*(7), 1073-1082. https://doi.org/10.1016/S0191-8869(01)00213-6

Hohaus, L., & Berah, E. (1996). Stress, achievement, marriage and social support: Effects on the psychological well-being of physicians entering mid-life/ mid-career. *Psychology and Health*, *11*(5), 715-731. https://doi.org/10.1080/08870449608405000

Holmes, T. H., & Rahe, R. H. (1967). The social readjustment rating scale. *Journal of Psychosomatic Research*, *11*(2), 213-218. https://doi.org/10.1016/0022-3999(67)90010-4

Hoque, N., Ahmed, H. A., Bhattacharyya, D. K., & Kalita, J. K. (2016). A Fuzzy Mutual Information-based Feature Selection Method for Classification. *Fuzzy Information and Engineering*, *8*(3), 355-384. https://doi.org/10.1016/j.fiae.2016.09.004

Hormone Health Network (2016). Learn answers to "What is Cortisol" | Hormone Health Network. Retrieved April 8, 2017, from http://www.hormone.org/hormones-and-health/what-do-hormones-do/cortisol

Horne, J. A., & Ostberg, O. (1976). A self-assessment questionnaire to determine morningness-eveningness in human circadian rhythms. *International Journal of Chrono-Biology*, *4*(April), 97-110.

Hossain, M. S., Huda, K., Rahman, S. M. S., & Ahmad, M. (2016). Implementation of an EOG based security system by analyzing eye movement patterns. *Proceedings of 2015 3rd International Conference on Advances in Electrical Engineering, ICAEE 2015*, 149-152. https://doi.org/10.1109/ICAEE.2015.7506818

Howard, S. (2012). One-way ANOVA. *Experimental Design and Analysis*, 171-190. Retrieved from http://www.stat.cmu.edu/~hseltman/309/Book/chapter7.pdf

Howarth, E., & Hoffman, M. S. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology (London, England : 1953).* https://doi.org/10.1111/j.2044-8295.1984.tb02785.x

Hsu, Y. J., Shih, J. L., & Chen, C. H. (2012). Emotion labyrinth: Learning to rationalize emotions through 3D game environment. *Proceedings of the 2012 IIAI International Conference on Advanced Applied Informatics, IIAIAAI 2012*, (1998), 153-158. https://doi.org/10.1109/IIAI-AAI.2012.39

Huang, J., Kumar, S. R., Mitra, M., Zhu, W.-J., & Zabih, R. (1997a). Image indexing using color correlograms. *IEEE Int. Conf. of Computer Vision and Pattern Recognition*, 762--768. https://doi.org/10.1109/CVPR.1997.609412

Huang, J., Kumar, S. R., Mitra, M., Zhu, W.-J., & Zabih, R. (1997b). Image indexing using color correlograms. In *Computer Vision and Pattern Recognition, 1997. Proceedings, 1997 IEEE Computer Society Conference on* (pp. 762-768). https://doi.org/10.1109/CVPR.1997.609412

Huang, N. E., & Wu, Z. (2008). A Review on Hilbert-Huang Transform : Method and Its Applications. *Reviews of Geophysics*, *46*(2007), 1-23. https://doi.org/10.1029/2007RG000228.1.INTRODUCTION

Hudgins, B., Parker, P., & Scott, R. N. (1993). A New Strategy for Multifunction Myoelectric Control. *IEEE Transactions on Biomedical Engineering*, *40*(1), 82-94. https://doi.org/10.1109/10.204774

IBM Statistics (n.d.). Generalized Linear Models. Retrieved November 26, 2017, from https://www.ibm.com/support/knowledgecenter/en/SSLVMB_22.0.0/com.ibm.spss.statistics.help/spss/advanced/idh_idd_genlin_typeofmodel.htm

IES Cities Project. (2016). Bristol Healthy Office - Application. Retrieved June 18, 2017, from https://play.google.com/store/apps/details?id=eu.iescities.HealthyOffice

IMDb.com. (2016). Retrieved December 31, 2016, from http://www.imdb.com/

Imholz, B. P. M., Montfrans, G. A. Van, Settels, J. J., Hoeven, G. M. A. Van Der, Karemaker, J. M., & Wieling, W. (1988). Continuous non-invasive blood pressure monitoring: Reliability of finapres device during the valsalva manoeuvre. *Cardiovascular Research.* https://doi.org/10.1093/cvrese/22.6.390

Imholz, B. P. M., Wieling, W., Van Montfrans, G. A., & Wesseling, K. H. (1998, June 1). Fifteen years experience with finger arterial pressure monitoring: Assessment of the technology. *Cardiovascular Research*. Oxford University Press. https://doi.org/10.1016/S0008-6363(98)00067-4

IMotions. (2016). GSR Pocket Guide The pocket guide, 1-36.

Infiniti, P. (2008a). *Phisiology Suite Biograph Infiniti*.

Infiniti, P. (2008b). ProComp Infiniti, ·(800), 1-45.

Investopedia (2017). Sampling. Retrieved November 1, 2017, from http://www.investopedia.com/terms/s/sampling.asp

IPLeiria (2009). Sampling Techniques - WikiEducacao. Retrieved October 1, 2017, from http://wiki.ued.ipleiria.pt/wikiEducacao/index.php/Técnicas_de_Amostragem

Ismailoglu, N., & Yalcin, T. (1999). Low-power design of a digital FM demodulator based on zero-cross detection at IF. In *IEEE Vehicular Technology Conference* (Vol. 50, pp. 810-813). https://doi.org/10.1109/VETECF.1999.798441

Iwasaki, K., Miyaki, T., & Rekimoto, J. (2010). AffectPhone: A Handset Device to Present User'ss Emotional State with Warmth / Coolness. *B-Interface*, *1*, 83-88.

Izard E., C. (1972). *Patterns of emotions; a new analysis of anxiety and depression [by] Carroll E. Izard. With chapters coauthored by Edmund S. Bartlett [and] Alan G. Marshall.* New York.

Jack, R. E., Garrod, O. G. B., & Schyns, P. G. (2014). Dynamic facial expressions of emotion transmit an evolving hierarchy of signals over time. *Current Biology*, *24*(2), 187-192.

Jamshidnejad, A., & Jamshidined, A. (2009). Facial emotion recognition for human computer interaction using a fuzzy model in the e-business. *2009 Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA)*, (July), 202-204. https://doi.org/10.1109/CITISIA.2009.5224214

Janković, D., & Stojanović, R. (2017). Flexible system for HRV analysis using PPG signal (pp. 705-712). Springer, Singapore. https://doi.org/10.1007/978-981-10-4166-2_106

Jaques, N., Taylor, S., Azaria, A., Ghandeharioun, A., Sano, A., & Picard, R. (2015). Predicting students' happiness from physiology, phone, mobility, and behavioral data. *2015 International Conference on Affective Computing and Intelligent Interaction, ACII 2015*, 222-228. https://doi.org/10.1109/ACII.2015.7344575

Jarkovska, D., Valesova, L., Chvojka, J., Benes, J., Sviglerova, J., Florova, B., ... Stengl, M. (2016). Heart rate variability in porcine progressive peritonitis-induced sepsis. *Frontiers in Physiology*, *6*(JAN). https://doi.org/10.3389/fphys.2015.00412

Jawbone (2017). UP by Jawbone | Fitness trackers for a healthier you. Retrieved July 22, 2017, from https://jawbone.com/?rf=bodymedia

Jennings, J. R., Bberg, W. K., Hutcheson, J. S., Obrist, P., Porges, S., & Turpin, G. (1981). Publication Guidelines for Heart Rate Studies in Man. *Psychophysiology*, *18*(3), 226-231. https://doi.org/10.1111/j.1469-8986.1981.tb03023.x

Jerritta, S., Murugappan, M., Nagarajan, R., & Wan, Kan (2011). Physiological signals based human emotion Recognition: a review. *Signal Processing and Its Applications (CSPA), 2011 IEEE 7th International Colloquium On*, 410-415. https://doi.org/10.1109/CSPA.2011.5759912

John, O. P., & Srivastava, S. (1999). Big Five Inventory (BFI). *Handbook of Personality: Theory and Research*, *2*, 102-138. https://doi.org/10.1525/fq.1998.51.4.04a00260

Johnston, D. W., Propper, C., & Shields, M. A. (2009). Comparing Subjective and Objective Measures of Health : Evidence from Hypertension for the Income / Health Gradient Comparing Subjective and Objective Measures of Health : Evidence from Hypertension for the Income / Health Gradient, *2737*(2737), 540-552.

Jones, N. A. (1992). Electroencephalogram Asymmetry during Emotionally Evocative Films and Its Relation to Positive and Negative Affectivity. *Brain and Cognition*, *299*(2), 280-299.

Kahn, R. L., & Antonucci, T. C. (1980). Convoys over the life course: Attachment, roles, and social support. *Life-Span Development and Behavior*, (3), 253-286.

Kamen, P. W., Krum, H., & Tonkin, A. M. (1996). Poincaré plot of heart rate variability allows quantitative display of parasympathetic nervous activity in humans. *Clinical Science (London, England : 1979)*, *91*(2), 201-208. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8795444

Kandel, E. R., Schwartz, J. H. H., & Jessell, T. M. (2000). *Principles of Neural Science* (Vol. 4). McGraw-hill New York. https://doi.org/10.1007/s13398-014-0173-7.2

Kataoka, H., Kano, H., Yoshida, H., Saijo, A., Yasuda, M., & Osumi, M. (1998). Development of a skin temperature measuring system for non-contact stress evaluation. In *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International*

Conference of the IEEE (Vol. 2, pp. 940-943).

Kawai, S., Takano, H., & Nakamura, K. (2013). Pupil diameter variation in positive and negative emotions with visual stimulus. *Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013*, 4179-4183. https://doi.org/10.1109/SMC.2013.712

Kemper, T. D. (1978). *A social interactional theory of emotion*. *American Sociological Review* (Vol. 61 (5)). Wiley New York.

Kemper, T. P. (1991). Predicting Emotions from Social Relations. *Social Psychology Quarterly*, *54*(4), 330-342. Retrieved from http://www.jstor.org/stable/2786845

Kessler, R. C., Price, R. H., & Wortman, C. B. (1985). Social Factors in Psychopathology: Stress, Social Support, and Coping Processes. *Annual Review of Psychology*, *36*(1), 531-572. https://doi.org/10.1146/annurev.ps.36.020185.002531

Khalfa, S., Isabelle, P., Jean-Pierre, B., & Manon, R. (2002). Event-related skin conductance responses to musical emotions in humans. *Neuroscience Letters*, *328*(2), 145-149. https://doi.org/10.1016/S0304-3940(02)00462-7

Kim, J., & André, E. (2008). Emotion recognition based on physiological changes in music listening. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *30*(12), 2067-2083. https://doi.org/10.1109/TPAMI.2008.26

Kim, K. H., Bang, S. W., & Kim, S. R. (2004). Emotion recognition system using short term monitoring of physiological signals. *Medical Biological Engineering and Computing*, *42*(Journal Article), 419-427. https://doi.org/10.1007/BF02344719

Kim, S., Anh, N., & Thi, N. (2016). Feature Extraction of Emotional States for EEG-based Rage Control. *39th International Conference on Telecommunications and Signal Processing (TSP)*, 361-364. https://doi.org/10.1109/TSP.2016.7760897

Kim, T. K. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology*, *68*(6), 540-546. https://doi.org/10.4097/kjae.2015.68.6.540

Kim, T. K., Kittler, J., & Cipolla, R. (2007). Discriminative learning and recognition of image set classes using canonical correlations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *29*(6), 1005-1018. https://doi.org/10.1109/TPAMI.2007.1037

Kirschbaum, C., Pirke, K. M., & Hellhammer, D. H. (1993). The 'Trier Social Stress Test'--a tool for investigating psychobiological stress responses in a laboratory setting. *Neuropsychobiology.* https://doi.org/119004

Knutson, B., Wolkowitz, O. M., Cole, S. W., Chan, T., D, P., Moore, E. A., ... Reus, V. I. (1998). Selective Alteration of Personality and Social Behavior by Serotonergic Intervention. *The American Journal OfPsychiatry*, *155*(3), 373-379. https://doi.org/10.1176/ajp.155.3.373

Koch, C. (2012). Study of the metric properties of the Portuguese version for Portugal of the Well-Being Questionnaire12 (W-BQ12) in women with pregnancy loss. *Latin American Journal of Nursing*, *20*(3). https://doi.org/10.1590/S0104-11692012000300019

Kohavi, R., & John, G. H. (1997). Wrappers for feature subset selection. *Artificial Intelligence*, *97*(1-2), 273-324. https://doi.org/10.1016/S0004-3702(97)00043-X

Koralewski (n.d.). Koralewski Elektronik. Retrieved July 16, 2017, from http://www.koralewski.de/english/index.php

Korf, R. E. (1993). Linear-space best-first search. *Artificial Intelligence*, *62*(1), 41-78. https://doi.org/10.1016/0004-3702(93)90045-D

Korkmaz, O. E., & Atasoy, A. (2015). Emotion Recognition from Speech Signal Using Mel-Frequency Cepstral Coefficients, 1254-1257.

Kosaka, T., Tanahashi, F., Matsui, N., & Fujitsuna, M. (2002). Current zero cross detection-based position sensorless control of synchronous reluctance motors. In *Industry Applications Conference, 2002. 37th IAS Annual Meeting. Conference Record of the* (Vol. 3, pp. 1610-1616 vol.3). https://doi.org/10.1109/IAS.2002.1043750

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biological Psychology*, *84*(3), 394-421. https://doi.org/10.1016/j.biopsycho.2010.03.010

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606-613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kumar, V., & Chadha, A. (2011). An empirical study of the applications of data mining techniques in higher education. *… Journal of Advanced Computer Science and ...*, *2*, 80-84. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.214.4184&rep=rep1&type=pdf#page=84%5Cnwww.ijacsa.thesai.org

Kusserow, M., Amft, O., & Troster, G. (2013). Monitoring Stress Arousal in the Wild. *IEEE Pervasive Computing*, *12*(2), 28-37. https://doi.org/10.1109/MPRV.2012.56

KWMC. (2016). Bristol Healthy Office. Retrieved June 18, 2017, from http://kwmc.org.uk/projects/bristolhealthyoffice/

LabX. (2017). Applied Science Laboratories 4000SU Eye Tracking System | For Sale | LabX Ad 3688478. Retrieved June 2, 2017, from http://www.labx.com/item/applied-science-laboratories-4000su-eye-tracking-system/3688478

Lack, L. C., Gradisar, M., Van Someren, E. J. W., Wright, H. R., & Lushington, K. (2008). The relationship between insomnia and body temperatures. *Sleep Medicine Reviews*, *12*(4), 307-317. https://doi.org/10.1016/j.smrv.2008.02.003

Laerd. (2013). Pearson Product-Moment Correlation. Retrieved November 3, 2017, from https://statistics.laerd.com/statistical-guides/pearson-correlation-coefficient-statistical-guide.php

Lai, H., Ramanathan, V., & Wechsler, H. (2008). Reliable face recognition using adaptive and robust correlation filters. *Computer Vision and Image Understanding*, *111*(3), 329-350. https://doi.org/10.1016/j.cviu.2008.01.003

Lake, D. E., Richman, J. S., Griffin, M. P., & Moorman, J. R. (2002). Sample entropy analysis of neonatal heart rate variability. *American Journal of Physiology - Regulatory, Integrative and Comparative Physiology*, *283*(3), R789-R797. https://doi.org/10.1152/ajpregu.00069.2002

Lalitha, S., Mudupu, A., Nandyala, B. V., & Munagala, R. (2015). Speech emotion recognition using DWT. In *2015 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)* (Vol. 6, pp. 1-4). IEEE. https://doi.org/10.1109/ICCIC.2015.7435630

Lane, N. D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., & Campbell, A. T. (2010). A survey of mobile phone sensing. *IEEE Communications Magazine*, *48*(9), 140-150. https://doi.org/10.1109/MCOM.2010.5560598

Lane, N., Mohammod, M., Lin, M., & Yang, X. (2011). Bewell: A smartphone application to monitor, model and promote wellbeing. *... Computing Technologies* .... Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.298.2259&rep=rep1&type=pdf

Lane, R. D., Reiman, E. M., Bradley, M. M., Lang, P. J., Ahern, G. L., Davidson, R. J., & Schwartz, G. E. (1997). Neuroanatomical correlates of pleasant and unpleasant emotion. *Neuropsychologia*, *35*(11), 1437-1444.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2005). International affective picture system (IAPS): Affective ratings of pictures and instruction manual. *Tech. Rep. A-6*.

Lang, Peter J. (1995). The emotion probe: Studies of motivation and attention. *American Psychologist*, *50*(5), 372-385. https://doi.org/10.1037//0003-066X.50.5.372

Lang, Peter J., Levin, D. N., Miller, G. A., & Kozak, M. J. (1983). Fear behavior, fear imagery, and the psychophysiology of emotion: The problem of affective response integration. *Journal of Abnormal Psychology*, *92*(3), 276-306. https://doi.org/10.1037/0021-843X.92.3.276

Larsen (1993). The Affect Intensity Measure (AIM).

Larsen, J. T., Mcgraw, P. A., & Cacioppo, J. T. (2001). Can People Feel Happy and Sad at the Same Time? *Journal of Personality and Social Psychology*, *81*(4), 684-696.

Larsen, R. J. (1984). Theory and Measurement of Affect Intensity As an Individual difference characteristic, *85*.

Larsen, Randy J., & Diener, E. (1987). Affect intensity as an individual difference characteristic: A review. *Journal of Research in Personality*, *21*(1), 1-39. https://doi.org/10.1016/0092-6566(87)90023-7

Lazarus, R. S., & Launier, R. (1978). Stress-Related Transactions between Person and Environment. In *Perspectives in Interactional Psychology* (pp. 287-327). Springer. https://doi.org/10.1007/978-1-4613-3997-7_12

Lee, C., Yoo, S. K., Park, Y., Kim, N., Jeong, K., & Lee, B. (2005). Using neural network to recognize human emotions from heart rate variability and skin resistance. *Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, *5*, 5523-5525. https://doi.org/10.1109/IEMBS.2005.1615734

Lee, S. H., Member, S., Ro, Y. M., & Member, S. (2016). Partial Matching of Facial Expression Sequence Using Over-Complete Transition Dictionary for Emotion Recognition, *7*(4), 389-408.

Lee, Y. C., Chou, C. C., Fang, W. C., & Huang, H. C. (2011). Portable sleep monitoring and awaking system based on EEG, ECG, tri-axis accelerometers and LED array panel. *Digest of Technical Papers - IEEE International Conference on Consumer Electronics*, 133-136. https://doi.org/10.1109/ICCE-Berlin.2011.6031867

Leite, W. L. (2005). Validation of Scores on the Marlowe-Crowne Social Desirability Scale and the Balanced Inventory of Desirable Responding. *Educational and Psychological Measurement*, *65*(1), 140-154. https://doi.org/10.1177/0013164404267285

Lemnaru, C., & Potolea, R. (2018). Evolutionary Cost-Sensitive Balancing: A Generic Method for Imbalanced Classification Problems (pp. 194-209). https://doi.org/10.1007/978-3-319-69710-9_14

Leonetti, A., & Foderaro, G. (2007). Beck Depression Inventory (BDI). *Apa.Org.* Retrieved from http://www.apa.org/pi/about/publications/caregivers/practice-settings/assessment/tools/beck-depression.aspx

Levenson, R. W., Ekman, P., & Friesen, W. V. (1990). Voluntary Facial Action Generates Emotion Specific Autom. *Psychophysiology.* https://doi.org/10.1111/j.1469-8986.1990.tb02330.x

Lewy, a J., & Sack, R. L. (1989). The dim light melatonin onset as a marker for circadian phase position. *Chronobiology International*, *6*(1), 93-102. https://doi.org/10.3109/07420528909059144

Leyvand, T., Meekhof, C., Wei, Y. C., Sun, J., & Guo, B. (2011). Kinect identity: technology and experience. *Computer*, *44*(4), 94-96. https://doi.org/10.1109/MC.2011.114

Li, Z., Shi, D., Wang, F., & Liu, F. (2016). Loneliness Recognition Based on Mobile Phone Data, (Isaeece), 165-172.

Lichtenstein, Antje; Oehme, A. K. S. J. T. (2008). *Comparing Two Emotion Models for Deriving Affective States from Physiological Data*. *Affect and Emotion in HCI, LNCS*. Retrieved from http://www.ulb.tu-darmstadt.de/tocs/59142804.pdf

LiKamWa, R., Liu, Y., Lane, N. D., & Zhong, L. (2013). MoodScope: Building a Mood Sensor from Smartphone Usage Patterns. *Proceeding of the 11th Annual International Conference on Mobile Systems, Applications, and Services - MobiSys '13*, 389. https://doi.org/10.1145/2462456.2464449

Lim, Y. G., Kim, K. K., & Park, K. S. (2006). ECG measurement on a chair without conductive contact. *IEEE Transactions on Biomedical Engineering*, *53*(5), 956-959. https://doi.org/10.1109/TBME.2006.872823

Linder, B. (2015). Toshiba unveils Silmee W20/W21 health trackers - Liliputing. Retrieved May 28, 2017, from https://liliputing.com/2015/07/toshiba-unveils-silmee-w20w21-health-trackers.html

Linh, T. (2008). EMOTIV EPOC+ 14 Channel Mobile EEG. Retrieved June 11, 2017, from https://www.emotiv.com/store/

Linton Instrumentation. (2011). Biopac Biopac MP100 - BIOPAC MP100 MP100 : Linton Instruments. Retrieved June 17, 2017, from http://www.lintoninst.co.uk/Products/tabid/63/ProdID/487/Language/en-US/CatID/127/Biopac_MP100_.aspx

Lisetti, C. L., & Nasoz, F. (2004). Using Noninvasive Wearable Computers to Recognize Human Emotions from Physiological Signals. *Journal of Applied Signal Processing*, *11*, 1672-1687. https://doi.org/10.1155/S1110865704406192

Liu, C., Yuen, J., & Torralba, A. (2015). Sift flow: Dense correspondence across scenes and its applications. *Dense Image Correspondences for Computer Vision*, 15-49. https://doi.org/10.1007/978-3-319-23048-1_2

Liu, L., Chen, X., Lu, Z., Cao, S., Wu, D., & Zhang, X. (2017). Development of an EMG-ACC-Based Upper, *25*(3), 244-253.

Liu, S., Zhang, Y., & Liu, K. (2014). Facial expression recognition under partial occlusion based on Weber Local Descriptor histogram and decision fusion. *Proceedings of the 33rd Chinese Control Conference, CCC 2014*, 4664-4668. https://doi.org/10.1109/ChiCC.2014.6895725

Liu, Y., Sourina, O., & Nguyen, M. K. (2010). Real-time EEG-based human emotion recognition and visualization. *Proceedings - 2010 International Conference on Cyberworlds, CW 2010*, 262-269. https://doi.org/10.1109/CW.2010.37

Long, X., Fonseca, P., Foussier, J., Haakma, R., & Aarts, R. M. (2014). Sleep and wake classification with actigraphy and respiratory effort using dynamic warping. *IEEE Journal of Biomedical and Health Informatics*, *18*(4), 1272-1284. https://doi.org/10.1109/JBHI.2013.2284610

Lopes, P. N., Salovey, P., & Straus, R. (2003). Emotional intelligence, personality, and the perceived quality of social relationships. *Personality and Individual Differences*, *35*(3), 641-658. https://doi.org/10.1016/S0191-8869(02)00242-8

Lu, Y., Lu, C., Qi, M., & Wang, S. (2010). Local Matching Algorithm for Face Recognition, 28-37.

Luefeng, C., Min, W. U., Mengtian, Z., Jinhua, S. H. E., & Kaoru, H. (2016). Dynamic Emotion Understanding Using FCM Based SVR in Human-Robot Interaction ∗, 7064-7069.

Lyons, R. G. (2004). *Understanding Digital Signal Processing*. *Angewandte Chemie International Edition* (Vol. 40). https://doi.org/10.1002/1521-3773(20010316)40:6<9823::AID-ANIE9823>3.3.CO;2-C

Machine Learning Group at the University of Waikato (n.d.). Weka 3 - Data Mining with Open Source Machine Learning Software in Java. Retrieved June 24, 2017, from http://www.cs.waikato.ac.nz/ml/weka/

Mackworth, A., & Goebel, R. (1998). Best-first Search. *Computational Intelligence*, 1-8.

Madan, A., Cebrian, M., Moturu, S., Farrahi, K., & Pentland, A. S. (2012). Sensing the health state of a community. *IEEE Pervasive Computing*, *11*(4), 36-45. https://doi.org/10.1109/MPRV.2011.79

Malik, A. S. (2009). Simulation-based analysis of the resolution and SNR properties of partial k-space EPI. *Concepts in Magnetic Resonance Part B: Magnetic Resonance Engineering*, *35*(4), 232-237. https://doi.org/10.1002/cmr.b.20147

Mandryk, R. L., & Atkins, M. S. (2007). A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. *International Journal of Human Computer Studies*, *65*(4), 329-347. https://doi.org/10.1016/j.ijhcs.2006.11.011

Mandryk, R. L., Atkins, M. S., & Inkpen, K. M. (2006). A continuous and objective evaluation of emotional experience with interactive play environments. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems CHI 06*, *2*(October 2016), 1027. https://doi.org/10.1145/1124772.1124926

Mandryk, R. L., & Inkpen, K. M. (2004). Physiological indicators for the evaluation of co-located collaborative play. *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work - CSCW '04*, (January 2004), 102. https://doi.org/10.1145/1031607.1031625

Manuck, S. B., Cohen, S., Rabin, B. S., Muldoon, M. F., & Bachen, E. A. (1991). Individual differences in cellular immune response to stress. *American Psychological Society*.

Maragos, P., & Sun, F. K. (1993). Measuring the Fractal Dimension of Signals: Morphological Covers and Iterative Optimization. *IEEE Transactions on Signal Processing*, *41*(1), 108. https://doi.org/10.1109/TSP.1993.193131

Markho, F. (2016). Major Influences in Households and Business Spaces - Wi-Fi , Telecommunication Masts Outputs and Electrical Pollution, (Epe), 20-22.

Martin (1000). Two-way ANOVA and ANCOVA. *None*, 1-6. https://doi.org/10.1002/9781118491683

Martinez-Nicolas, A., Ortiz-Tudela, E., Rol, M. A., & Madrid, J. A. (2013a). Uncovering Different Masking Factors on Wrist Skin Temperature Rhythm in Free-Living Subjects. *PLoS ONE*, *8*(4), e61142. https://doi.org/10.1371/journal.pone.0061142

Martinez-Nicolas, A., Ortiz-Tudela, E., Rol, M. A., & Madrid, J. A. (2013b). Uncovering Different Masking Factors on Wrist Skin Temperature Rhythm in Free-Living Subjects. *PLoS ONE*, *8*(4), e61142. https://doi.org/10.1371/journal.pone.0061142

Mason, J. W. (1968). A review of psychoendocrine research on the sympathetic-adrenal medullary system. *Psychosomatic Medicine*, *30*(5), Suppl:631-653. https://doi.org/1968/09000

Matiko, J. W., Beeby, S. P., & Tudor, J. (2014). Fuzzy logic based emotion classification. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 4389-4393). IEEE. https://doi.org/10.1109/ICASSP.2014.6854431

Matlovic, T., Gaspar, P., Moro, R., Simko, J., & Bielikova, M. (2016). Emotion Detection Using Facial Expressions Recognition and EEG. *11th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP)*, 18-23. https://doi.org/10.1109/SMAP.2016.7753378

Matsunaga, K. (1990). Psychology of the Pupil Movement. Nakanishiya publishing.

Mayampurath, A., Volchenboum, S. L., & Sanchez-Pinto, L. N. (2018). Using photoplethysmography data to estimate heart rate variability and its association with organ dysfunction in pediatric oncology patients. *Npj Digital Medicine*, *1*(1), 29. https://doi.org/10.1038/s41746-018-0038-0

McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, *60*(2), 175-215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McLeod, S. (2010). SRRS - Stressful Life Events and Daily Hassles | Simply Psychology. Retrieved June 22, 2017, from https://www.simplypsychology.org/SRRS.html

McNair, D., Lorr, M., & Droppleman, L. (1989). Profile of Mood States (POMS).

McNulty W, Gevirtz R, Berkoff G, H. D. (1994). Needle EMG Pevaluation of trigger point response to a psychological stressor. Psychophysiol 31,313-316, 1994.pdf. *Psychophysiology*, 31(3), 313-316.

Medtronic. (2015). HxM | Zephyr™ Performance Systems. Retrieved June 16, 2017, from https://www.zephyranywhere.com/resources/hxm

Mehta, S. K., Super, D. M., Salvator, A., Fradley, L. G., Connuck, D., & Kaufman, E. S. (2002). Heart rate variability by triangular index in infants exposed prenatally to cocaine. *Annals of Noninvasive Electrocardiology : The Official Journal of the International Society for*

Holter and Noninvasive Electrocardiology, Inc, *7*(4), 374-378. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12431317

Merens, W., Willem Van der Does, A. J., & Spinhoven, P. (2007). The effects of serotonin manipulations on emotional information processing and mood. *Journal of Affective Disorders*, *103*(1-3), 43-62. https://doi.org/10.1016/j.jad.2007.01.032

Microsoft (2017a). Kinect - Windows application development. Retrieved June 30, 2017, from https://developer.microsoft.com/pt-pt/windows/kinect

Microsoft (2017b). Microsoft Cognitive Services - Emotion API. Retrieved December 31, 2016, from https://www.microsoft.com/cognitive-services/en-us/emotion-api

Mietus, J., Peng, C.-K., Henry, I., Goldsmith, R., & AL, G. (2015). pNNx: Time Domain Heart Rate Variability Analysis. Retrieved October 15, 2017, from https://physionet.org/physiotools/pNNx/

Mill, S., Road, R., Ardsley, P. O. B., & York, N. (n.d.). MicroMini-Motionlogger ® Actigraph Interface/Connector with ACT Operational Software Micro Motionlogger Sleep Watch, 1-6. Retrieved from www.ambulatory-monitoring.com

Miller, G. A., Levin, D. N., Kozak, M. J., Edwin, E., McLean, A., & Lang, P. J. (1987). Individual Differences in Imagery and the Psychophysiology of Emotion. *Cognition and Emotion*, *1*(4), 367-390. https://doi.org/10.1080/02699938708408058

Miluzzo, E., Lane, N. D., Fodor, K., Peterson, R., Lu, H., Musolesi, M., ... Campbell, A. T. (2008). Sensing meets mobile social networks. *ACM Conference on Embedded Network Sensor Systems*, 337-350. https://doi.org/10.1145/1460412.1460445

Mind Media (n.d.). Biofeedback and neurofeedback systems | Oximetry Sensor. Retrieved August 15, 2017, from http://www.mindmedia.info/CMS2014/en/products/sensors/oximetry-sensor

Mokhayeri, F., & Toosizadeh, S. (2011). Mental Stress Detection Using Physiological Signals Based on Soft Computing Techniques. *18th Iranian Conference on BioMedical Engineering*, (December), 232-237. https://doi.org/10.1109/ICBME.2011.6168563

Monteiro, S., Tavares, J., Pereira, A., & Universidade de Aveiro, P. (2012). Portuguese adaptation of the scale measuring manifestations of psychological well-being with university students - emmbep. *Psychology, Health & Illness*, *13*(1), 66-77.

Morris, T. L., & Miller, J. C. (1996). Electrooculographic and performance indices of fatigue during simulated flight. *Biological Psychology*, *42*(3), 343-360. https://doi.org/10.1016/0301-0511(95)05166-X

Mosby's Medical Dictionary (2009). peripheral vascular resistance. Retrieved April 18, 2017, from http://medical-dictionary.thefreedictionary.com/peripheral+vascular+resistance

Moskowitz, D. S., Pinard, G., Zuroff, D. C., Annable, L., & Young, S. N. (2001). The effect of tryptophan on social interaction in everyday life: A placebo-controlled study. *Neuropsychopharmacology*, *25*(2), 277-289. https://doi.org/10.1016/S0893-133X(01)00219-6

Moturu, S. T., Khayal, I., Aharony, N., Pan, W., & Pentland, A. S. (2011). Using Social Sensing to Understand the Links Between Sleep, Mood, and Sociability. Retrieved from http://hd.media.mit.edu/tech-reports/TR-670.pdf movisens GmbH. (2018a). EdaMove 3. Retrieved June 24, 2018, from https://www.movisens.com/en/products/edamove-3/

movisens GmbH. (2018b). EdaMove 3 - EDA and Activity Sensor. Retrieved November 3, 2018, from https://www.movisens.com/en/products/eda-and-activity-sensor-move-3/

Mower, E., Matari, M. J., & Narayanan, S. (2011). A Framework for Automatic Human Emotion Classification Using Emotion Profiles. *Ieee Transactions on Audio, Speech, and Language Processing*, *19*(5), 1057-1070. https://doi.org/10.1109/TASL.2010.2076804

Muaremi, A., Arnrich, B., & Tröster, G. (2012). A Survey on Measuring Happiness with Smart Phones. *6th International Workshop on Ubiquitous Health and Wellness .UbiHealth*, (January). Retrieved from http://www.researchgate.net/publication/235834264_A_Survey_on_Measuring_Happiness_with_Smart_Phones/file/9fcfd513f50c5229f9.pdf

Muaremi, A., Bexheti, A., Gravenhorst, F., Arnrich, B., & Tröster, G. (2014). Monitoring the Impact of Stress on the Sleep Patterns of Pilgrims using Wearable Sensors. *IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI)*, 3-6. https://doi.org/10.1109/BHI.2014.6864335

Müller, G., & Martin, G. (1992). [Quantitative measurement of peripheral vascular resistance with a cavernous sinus ultrasound instrument (Cavomat)]. *VASA. Supplementum*, *36*, 25-28. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1529421

Murad, U., & Malkawi, M. (2012). Artificial neuro fuzzy logic system for detecting human emotions. *IEEE CITS 2012 - 2012 International Conference on Computer, Information and Telecommunication Systems*, 1-13. https://doi.org/10.1109/CITS.2012.6220388

Murai, M., Nakayama, M., & Shimizu, Y. (1998). A correlation of pupillary changes and subjective evaluation to television programs. *IEICE Technical Report. Education Technology*, *98*(156), 7-14. https://doi.org/10.3169/itej.52.1748

Murali, S., Rincon, F., & Atienza, D. (2015). A wearable device for physical and emotional health monitoring. *2015 Computing in Cardiology Conference (CinC)*, 121-124. https://doi.org/10.1109/CIC.2015.7408601

Myers, & Briggs (n.d.). The Myers and Briggs Personality Test | Online Personality Tests. Retrieved July 1, 2017, from http://www.onlinepersonalitytests.org/mbti

Natus Medical Inc (2017). Natus Medical Incorporated - Grass. Retrieved from http://www.natus.com/index.cfm?page=company_1&crid=753

Nawasalkar, R. K., Lawange, H. R., Gupta, S. D., Butey, P. K., & Email, W. S. (2013). Study of comparison of human bio-signals for emotion detection using HCI. *International Journal of Emerging Trends & Technology in Computer Science*, *2*(2), 449-452.

Neurosky. (2017). EEG Headsets | NeuroSky Store. Retrieved June 16, 2017, from http://neurosky.com/biosensors/eeg-sensor/biosensors/

NeuroSky. (2017). Development Tools for PC/Mac. Retrieved June 30, 2017, from http://developer.neurosky.com/docs/doku.php?id=mdt2.5

Nichkova, M. I., Huisman, H., Wynveen, P. M., Marc, D. T., Olson, K. L., & Kellermann, G. H. (2012). Evaluation of a novel ELISA for serotonin: Urinary serotonin as a potential biomarker for depression. *Analytical and Bioanalytical Chemistry*, *402*(4), 1593-1600. https://doi.org/10.1007/s00216-011-5583-1

Nicolai, T., & Kenn, H. (2007). About the relationship between people and discoverable Bluetooth devices in urban environments. In *Proceedings of the 4th international conference on mobile technology, applications, and systems and the 1st international symposium on Computer human interaction in mobile technology - Mobility '07* (p. 72). New York, New York, USA: ACM Press. https://doi.org/10.1145/1378063.1378076

Niedermeyer, E., & Silva, F. H. L. da. (2005). *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields* (Vol. 1). Retrieved from https://books.google.fr/books?id=tndqYGPHQdEC

Niemic, C. P., Kirk, A., Brown, W., & Ph, D. (2002). Studies of Emotion: A Theoretical and Emperical Review of Psychophysiological Studies of Emotion. *Journal of Undergraduate Research*, 15-18.

Noldus. (2017). Facial expression recognition software: FaceReader. Retrieved March 12, 2017, from http://www.noldus.com/human-behavior-research/products/facereader

Norman, D. A. (2002). Emotion & Design: Attractive things work better - jnd.org, (October). https://doi.org/10.1145/543434.543435

Nwe, L., Wei, S., Silva, D., Liyanage, C., Silva, D., Speech, L. C., ... Member, S. (2001). Speech based emotion classification.

Omar, D. A. (2006). EMOTIONS - Articles.com Retrieved April 9, 2017, from http://www.artigos.com/artigos/13851-emocoes

WHO. (2016). WHO | Health. Retrieved from http://www.who.int/about/mission/en/

OriginLab Corporation (n.d.). Origin Data Analysis and Graphing Software Exercise. Retrieved July 2, 2017, from http://www.originlab.com/Origin

Ornelas, J. (1996). Social support and mental illness. *Psychological Analysis*, *2-3 (XIV)*, 263-268.

Oswald, A. J., & Wu, S. (2010). Objective Confirmation of Subjective Measures of Human Well-Being: Evidence from the U.S.A. *Science*, *327*(5965), 576-579. https://doi.org/10.1126/science.1180606

Oura Crew (2017). How to Measure Heart Rate Variability? | OURA HRV Tracking. Retrieved September 9, 2018, from https://blog.ouraring.com/blog/how-to-measure-heart-rate-variability/

Ouwerkerk, M., Pasveer, F., & Langereis, G. (2008). Unobtrusive sensing of psychophysiological parameters. *Probing Experience*, 163-193. https://doi.org/10.1007/978-1-4020-6593-4_15

P. Ekman, R. W. Levenson, and W. V. F. (1983). Autonomic-Nervous-System-Activity-Distinguishes-Among-Emotio.pdf. *Science*, *221*, 1208-1210.

Padmanabhan, M., Murali, S., Rincon, F., & Atienza, D. (2015). Energy-aware embedded classifier design for real-time emotion analysis. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (Vol. 2015-Novem, pp. 2275-2278). IEEE. https://doi.org/10.1109/EMBC.2015.7318846

Pagulayan, R. J., Keeker, K., Wixon, D., Romero, R., & Fuller, T. (2012). User-centered Design in Games. *The Human-Computer Interaction Handbook: Fundamentals, Evolving Technologies and Emerging Applications*, (January), 883-906. https://doi.org/10.1088/1751-8113/44/8/085201

Pagulayan, R., Keeker, K., Fuller, T., Wixon, D., Romero, R., & Gunn, D. (2012). User-Centered Design in Games, (October), 795-822. https://doi.org/10.1201/b11963-39

Pais-Ribeiro, J. L. (1999). Social support satisfaction scale (ESSS). *Psychological Analysis*, *3*(17), 547-558. Retrieved from http://www.scielo.oces.mctes.pt/scielo.php?pid=S0870-82311999000300010&script=sci_arttext%5Cnhttps://repositorio-aberto.up.pt/bitstream/10216/5544/2/80971.pdf

Pais-Ribeiro, J., Silva, I., Ferreira, T., Martins, A., Meneses, R., & Baltar, M. (2007). Validation study of a Portuguese version of the Hospital Anxiety and Depression Scale. *Psychol Health Med*, *12*(2), 225-227. https://doi.org/10.1080/13548500500524088

Panthong, R., & Srivihok, A. (2015). Wrapper Feature Subset Selection for Dimension Reduction Based on Ensemble Learning Algorithm. *Procedia Computer Science*, *72*, 162-169. https://doi.org/10.1016/j.procs.2015.12.117

Pantic, M., Sebe, N., Cohn, J. F., & Huang, T. (2005). Affective multimodal human-computer interaction. *Proceedings of the 13th Annual ACM International Conference on Multimedia - MULTIMEDIA '05*, 669. https://doi.org/10.1145/1101149.1101299

Papamatthaiakis, G., Polyzos, G. C., & Xylomenos, G. (2010). Monitoring and modeling simple everyday activities of the elderly at home. *2010 7th IEEE Consumer Communications and Networking Conference, CCNC 2010.* https://doi.org/10.1109/CCNC.2010.5421717

Park, C., Ryu, J., Sohn, J., & Cho, H. (2007). An emotion expression system for the emotional robot. *Proceedings of the International Symposium on Consumer Electronics, ISCE.* https://doi.org/10.1109/ISCE.2007.4382195

Partala, T., & Surakka, V. (2003). Pupil size variation as an indication of affective processing. *International Journal of Human Computer Studies*, *59*(1-2), 185-198. https://doi.org/10.1016/S1071-5819(03)00017-X

Partala, T., Surakka, V., & Vanhala, T. (2005). Person-independent estimation of emotional experiences from facial expressions. *Proceedings of the 10th International Conference on Intelligent User Interfaces - IUI '05*, 246. https://doi.org/10.1145/1040830.1040883

Paschero, M., Del Vescovo, G., Benucci, L., Rizzi, A., Santello, M., Fabbri, G., & Mascioli, F. M. F. (2012). A real time classifier for emotion and stress recognition in a vehicle driver. *IEEE International Symposium on Industrial Electronics*, 1690-1695. https://doi.org/10.1109/ISIE.2012.6237345

Pearson, K. (1901). Principal components analysis. *The London*. Retrieved from http://www.botany.hawaii.edu/bot644/Manly_multivariate.pdf%5Cnpapers2://publication/uuid/8268B57E-298A-4D21-A76D-CE842083AA61

Pechorro, P., Marôco, J., Poiares, C., & Vieira, R. X. (2011). Validation of the Rosenberg Self-Esteem Scale with Portuguese adolescents in forensic and school context. *Archives of Medicine*, *25*(5-6), 174-179.

Peirce, R. S., Frone, M. R., Russell, M., Cooper, M. L., & Mudar, P. (2000). A longitudinal model of social contact, social support, depression, and alcohol use. *Health Psychol*, *19*(1), 28-38. https://doi.org/10.1037/0278-6133.19.1.28

Pentland, A. (2005). Socially aware computation and communication. *Computer*, *38*(3), 33-40. https://doi.org/10.1109/MC.2005.104

Penzel, T., Kantelhardt, J. W., Grote, L., Peter, J.-H., & Bunde, A. (2003). Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea. *IEEE Transactions on Bio-Medical Engineering*, *50*(10), 1143-1151. https://doi.org/10.1109/TBME.2003.817636

Peper, E., Harvey, R., Lin, I., Tylova, H., & Moss, D. (2007). Is There More to Blood Volume Pulse Than Heart Rate Variability , Respiratory Sinus Arrhythmia , and Cardiorespiratory Synchrony ? *Biofedback*, *35*(2), 54-61.

Perdiz, J., Pires, G., & Nunes, U. J. (2017). Emotional state detection based on EMG and EOG biosignals: A short survey. In *2017 IEEE 5th English Meeting on Bioengineering (ENBENG)* (pp. 1-4). IEEE. https://doi.org/10.1109/ENBENG.2017.7889451

Pereira, M. G. (2003). Revised Dyadic Adjustment Scale - Research Version.

Phinyomark, A., Phukpattaranont, P., & Limsakul, C. (2012). Feature reduction and selection for EMG signal classification. *Expert Systems with Applications*, *39*(8), 7420-7431. https://doi.org/10.1016/j.eswa.2012.01.102

Picard, R., & Klein, J. (2002). Computers that recognize and respond to user emotion: theoretical and practical implications. *Interacting with Computers*, *14*(Spitz 1945), 141-169.

Picard, R. W. (1995). *Affective computing*. *Social security bulletin* (Vol. 70). MIT press Cambridge. https://doi.org/10.1007/BF01238028

Picard, R.W., Vyzas, E., & Healey, J. (2001). Toward machine emotional intelligence: analysis of affective\nphysiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *23*(10), 1175-1191. https://doi.org/10.1109/34.954607

Picard, Rosalind W. (2000). *Affective Computing*. MIT Press.

Picard, Rosalind W., Vyzas, E., & Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *23*(10), 1175-1191. https://doi.org/10.1109/34.954607

Pleger, E., Wilke, A., Glaser, T., Müller, E., & Vogel, J. (1989). [Practical experiences with 2 oscillatory measuring procedures, Siregnost FD 5 and custo vit, in the assessment of chronic airway obstruction]. *Pneumologie (Stuttgart, Germany)*, *43*(7), 353-357. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/2780527

plux. (n.d.). biosignalsplux | wearable body sensing platform. Retrieved August 18, 2017, from http://biosignalsplux.com/index.php/en/

Plux. (2017). BVP Blood Volume Pulse. Retrieved April 17, 2017, from http://biosignalsplux.com/index.php/en/bvp-blood-volume-pulse

Pocinho, M. (2009). Estatistica: teoria e exercicios passo a passo. Volume I. *Ismt*, *I*, 1-82. Retrieved from http://docentes.ismt.pt/~m_pocinho/Sebenta_estatistica I.pdf

Poh, M.-Z., Swenson, N. C., & Picard, R. W. (2010). A wearable sensor for unobtrusive, long-term assesment of electrodermal activity. *IEEE Transactions on Biomedical Engineering*, *57*(5), 1243-1252. https://doi.org/10.1109/tbme.2009.2038487

Pollak, M. H., & Obrist, P. A. (1983). Aortic-Radial Pulse Transit Time and ECG Q-Wave to Radial Pulse Wave Interval as Indices of Beat-By-Beat Blood Pressure Change. *Psychophysiology*, *20*(1), 21-28.

Poole, A., & Ball, L. J. (2005). Eye Tracking in Human-Computer Interaction and Usability

Research: Current Status and Future Prospects. *Encyclopedia of Human-Computer Interaction*, 211-219. https://doi.org/10.4018/978-1-59140-562-7

Porges, S. W. (1995). Cardiac vagal tone: A physiological index of stress. *Neuroscience and Biobehavioral Reviews*, *19*(2), 225-233. https://doi.org/10.1016/0149-7634(94)00066-A

Rachuri, K. K., Mascolo, C., Rentfrow, P. J., & Longworth, C. (2010). EmotionSense : A Mobile Phones based Adaptive Platform for Experimental Social Psychology Research. *International Studies*, *10*, 281--290. https://doi.org/10.1145/1864349.1864393

Radzyk, J. (2014). Validation of a New Social Well - Being Questionnaire.

Ramirez, R., Ramirez, R., & Vamvakousis, Z. (2015). Detecting emotion from EEG signals using the emotive epoc device Detecting Emotion from EEG Signals Using the Emotive Epoc Device, (October), 175-184. https://doi.org/10.1007/978-3-642-35139-6

Ramshur, J. T. (2010). Design, evaluation and application of heart rate variability analysis software (HRVAS). Retrieved from https://scholar.google.ca/scholar?hl=en&q=DESIGN%2C+EVALUATION%2C+AND+APPLICATION+OF+HEART+RATE+VARIABILITY+ANALYSIS+SOFTWARE+%28HRVAS%29&btnG=&as_sdt=1%2C5&as_sdtp=

Rani, P., Liu, C., Sarkar, N., & Vanman, E. (2006). An empirical study of machine learning techniques for affect recognition in human-robot interaction. *Pattern Analysis and Applications*, *9*(1), 58-69. https://doi.org/10.1007/s10044-006-0025-y

Rani, P., & Sarkar, N. (2006). A new approach to implicit human-robot interaction using affective cues. *Mobile Robots, Towards New Applications*, *3866113145*(December), 233-252. https://doi.org/10.5772/4693

Rani, P., Science, C., Sarkar, N., Smith, C. a, & Adams, J. a. (2003). Affective Communication for Implicit Human-. *Proceedings. ICRA'03. IEEE International Conference*, 2382-2387.

Raschka, S. (2014). Linear Discriminant Analysis. Retrieved from http://sebastianraschka.com/Articles/2014_python_lda.html

Raspberry Pi Foundation (n.d.). Raspberry Pi. Retrieved November 18, 2018, from https://www.raspberrypi.org/

Raudonis, V. (2013). Evaluation of Human Emotion from Eye Motions. *International Journal of Advanced Computer Science and Applications*, *4*(8), 79-84. https://doi.org/10.14569/IJACSA.2013.040812

Ravichandran, R., Saba, E., Chen, K. Y., Goel, M., Gupta, S., & Patel, S. N. (2015). WiBreathe: Estimating respiration rate using wireless signals in natural settings in the home. *2015 IEEE International Conference on Pervasive Computing and Communications, PerCom 2015*, *16*, 131-139. https://doi.org/10.1109/PERCOM.2015.7146519

Recognition, F. E. (2009). Facial Expression Recognition. *Analysis*, *77*(6), 1507-1513. https://doi.org/10.1016/j.anbehav.2009.02.024

Rehabilitation Institute of Chicago (2014). WHO Quality of Life-BREF (WHOQOL-BREF). *Rehabmeasures.Org.* Retrieved from http://www.rehabmeasures.org/Lists/RehabMeasures/PrintView.aspx?ID=937

Rehm, M., Bee, N., & André, E. (2008). Wave like an Egyptian: accelerometer based gesture recognition for culture specific interactions. *Proceedings of the 22nd British HCI Group*

Annual Conference on People and Computers: Culture, Creativity, Interaction, 13-22. Retrieved from http://dl.acm.org/citation.cfm?id=1531514.1531517

Reis, C. (2016). MBTI - Myers Briggs Test - Take the Test Online! - E-Konomist. Retrieved July 1, 2017, from http://www.e-konomista.pt/artigo/myers-briggs-test/

Reis, H. T., Gable, S. L., Keyes, C. L. M., & Haidt, J. (2003). Toward a positive psychology of relationships. In *Flourishing: Positive psychology and the well-lived life* (pp. 129-159). Washington: American Psychological Association. https://doi.org/10.1037/10594-006

Rigamonti, R., Brown, M. A., & Lepetit, V. (2011). Are sparse representations really relevant for image classification? *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1545-1552. https://doi.org/10.1109/CVPR.2011.5995313

Rigas, G. (2007). User Modeling 2007, *4511*(June 2014), 1-6. https://doi.org/10.1007/978-3-540-73078-1

Rissanen, J. (2013). Cisbio Bioassays and Orion Diagnostica Oy sign an agreement for steroid radioimmunoassays - www.oriondiagnostica.com. Retrieved June 11, 2017, from http://www.oriondiagnostica.com/News-and-events/Cisbio-Bioassays-and-Orion-Diagnostica-Oy-sign-an-agreement-for-steroid-radioimmunoassays/

Ritz, T., Steptoe, A., DeWilde, S., & Costa, M. (2000). Emotions and Stress Increase Respiratory Resistance in Asthma. *Psychosomatic Medicine*, *62*(3), 401-412. https://doi.org/10.1097/00006842-200005000-00014

Robbins, B. D., & Parlavecchio, H. (2006). The Unwanted Exposure of the Self: A Phenomenological Study of Embarrassment. *The Humanistic Psychologist*, *34*(4), 321-345. https://doi.org/10.1207/s15473333thp3404_3

Robins, R. W., & Tracy, J. L. (2004). Putting the Self Into Self-Conscious Emotions: A Theoretical Model. *Psychological Inquiry*, *15*, 103-125.

Rodin, J., & Salovey, P. (1989). Health Psychology. *Annual Review of Psychology*, *40*(1), 533-579. https://doi.org/10.1146/annurev.ps.40.020189.002533

Rosenberg, M. (1965). Society and the Adolescent Self-Image. *1965.* https://doi.org/10.1515/9781400876136

Rosmalen, J. G. M., Bos, E. H., & de Jonge, P. (2012). Validation of the Long-term Difficulties Inventory (LDI) and the List of Threatening Experiences (LTE) as measures of stress in epidemiological population-based cohort studies. *Psychological Medicine*, *42*(12), 2599-2608. https://doi.org/10.1017/S0033291712000608

Rudolph, H., & Pnt, R. (2004). HANS RUDOLPH, inc.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161-1178. https://doi.org/10.1037/h0077714

Russell, J. A., Weiss, A., & Mendelsohn, G. A. (1989). Affect Grid: A single-item scale of pleasure and arousal. *Journal of Personality and Social Psychology*, *57*(3), 493-502. https://doi.org/10.1037/0022-3514.57.3.493

Saha, S., Datta, S., Konar, A., & Janarthanan, R. (2014). A study on emotion recognition from body gestures using Kinect sensor. *Communications and Signal Processing (ICCSP), 2014 International Conference On*, 56-60. https://doi.org/10.1109/ICCSP.2014.6949798

Salimetrics (n.d.). Melatonin Testing in Saliva & Salivary Melatonin Research. Retrieved

April 22, 2017, from https://www.salimetrics.com/biomarker/melatonin

Sander, B., Markvart, J., Kessel, L., Argyraki, A., & Johnsen, K. (2015). Can sleep quality and wellbeing be improved by changing the indoor lighting in the homes of healthy, elderly citizens? *Chronobiology International*, *0528*(December), 1-12. https://doi.org/10.3109/07420528.2015.1056304

Sanders, J. L., & Brizzolara, M. S. (1982). Relationships between Weather and Mood. *The Journal of General Psychology*, *107*(1), 155-156. https://doi.org/10.1080/00221309.1982.9709917

Sano, A., & Eng, B. (2016). Measuring College Students' Sleep, Stress, Mental Health and Wellbeing with Wearable Sensors and Mobile Phones, (2003), 182.

Sano, A., & Picard, R. W. (2013a). Recognition of sleep dependent memory consolidation with multi-modal sensor data. *2013 IEEE International Conference on Body Sensor Networks, BSN 2013.* https://doi.org/10.1109/BSN.2013.6575479

Sano, A., & Picard, R. W. (2013b). Stress Recognition using Wearable Sensors and Mobile Phones. *Humaine Association Conference on Affective Computing and Intelligent Interaction Stress*, 671-676. https://doi.org/10.1109/ACII.2013.117

Sano, A., & Picard, R. W. (2014). Comparison of sleep-wake classification using electroencephalogram and wrist-worn multi-modal sensor data. *Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, *2014*, 930-933. https://doi.org/10.1109/EMBC.2014.6943744

Santos, P. J., & Maia, J. (2003). Confirmatory factorial analysis and preliminary validation of a Portuguese version of Rosenberg's self-esteem scale. *Psicologia: Teoria, Investigaçäo e Prática*. Porto: Faculdade de Letras, Secção autónoma de Educação, Universidade do Porto.

Sarabia, J. A., Rol, M. A., Mendiola, P., & Madrid, J. A. (2008). Circadian rhythm of wrist temperature in normal-living subjects. A candidate of new index of the circadian system. *Physiology and Behavior*, *95*(4), 570-580. https://doi.org/10.1016/j.physbeh.2008.08.005

Sarason, I. G., Sarason, B. R., Potter, E. H., & Antoni, M. H. (1985). Life events, social support, and illness. *Psychosomatic Medicine*, *47*(2), 156-163. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/17992965

Sarason, I. G., Sarason, B. R., Shearin, E. N., & Pierce, G. R. (1987). Assessing social support: The Social Support Questionnaire. *Journal of Social and Personal Relationships*, *4*(l), 497-510.

Sarstedt (n.d.). *Cortisol-Salivette: Evaluation Report*.

Sato, N.; Obuchi, Y. . (2007). Emotion Recognition using Mel- Frequency Cepstral Coefficients. *Journal of Natural Language Processing*, 83-96.

Schachter, J. (1957). Pain, Fear, and Anger in Hypertensives and Normotensives: A Psychophysiological Study. *Psychosomatic Medicine*, *19*(1), 17-29. Retrieved from http://www.psychosomaticmedicine.org/cgi/content/abstract/19/1/17

Schapire, R. E. (2013). Explaining adaboost. *Empirical Inference: Festschrift in Honor of Vladimir N. Vapnik*, 37-52. https://doi.org/10.1007/978-3-642-41136-6_5

Scheer, F., van Doornen, L., & Buijs, R. (1999). Light and diurnal cycle affect human heart rate:

Possible role for the circadian pacemaker. *Journal of Biological Rhythms*, *14*(3), 202-212. https://doi.org/10.1177/074873099129000614

Scherer, K. R., & Ekman, P. (1984). On the nature and function of emotion: A component process approach. In Press Psychology (Ed.), *Approaches To Emotion* (pp. 294-317). New Jersey: Taylor & Francis. Retrieved from https://books.google.com/books?hl=fr&lr=&id=k0mhAwAAQBAJ&pgis=1

Schiele, B. C., Baker, A. B., & Hathaway, S. R. (1943). The Minnesota multiphasic personality inventory. *Journal-Lancet*, *63*, 292-297. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=1944-03192-001&site=ehost-live

Schulze, L., Renneberg, B., & Lobmaier, J. S. (2013). Gaze perception in social anxiety and social anxiety disorder. *Frontiers in Human Neuroscience*, *7.* https://doi.org/10.3389/fnhum.2013.00872

Schumm, J., & Arnrich, B. (2012). ecG Monitoring in an airplane Seat:, 28-34.

Schumm, J., B??chlin, M., Setz, C., Arnrich, B., Roggen, D., & Tr??ster, G. (2008). Effect of movements on the electrodermal response after a startle event. *Proceedings of the 2nd International Conference on Pervasive Computing Technologies for Healthcare 2008, PervasiveHealth*, (June 2017), 315-318. https://doi.org/10.1109/PCTHEALTH.2008.4571101

Schumm, J., Setz, C., B??chlin, M., B??chler, M., Arnrich, B., & Tr??ster, G. (2010). Unobtrusive physiological monitoring in an airplane seat. *Personal and Ubiquitous Computing*, *14*(6), 541-550. https://doi.org/10.1007/s00779-009-0272-1

Schwartz, G. E., Weinberger, D. a, & Singer, J. a. (1981). Cardiovascular differentiation of happiness, sadness, anger, and fear following imagery and exercise. *Psychosomatic Medicine*, *43*(4), 343-364. https://doi.org/10.1097/00006842-198108000-00007

Sebe, N., Cohen, I., Gevers, T., & Huang, T. S. (2006). Emotion recognition based on joint visual and audio cues. *Proceedings - International Conference on Pattern Recognition*, *1*, 1136-1139. https://doi.org/10.1109/ICPR.2006.489

Sela, I., Shinar, Z., & Tavakolian, K. (2016). Measuring Left Ventricular Ejection Time Using Under-the-Mattress Sensor. *Computing in Cardiology*, (Figure 1), 665-668.

Seligman, M. E. (2011). *Flourish: A visionary vew understanding of happiness and well-being*. Sydney: Nicholas Brealey Publishing.

Setz, C., Arnrich, B., Schumm, J., Marca, R. La, Tr, G., & Ehlert, U. (2010). Using a Wearable EDA Device. *Technologynology*, *14*(2), 410-417.

Shan, C., Gong, S., & McOwan, P. W. (2009). Facial expression recognition based on Local Binary Patterns: A comprehensive study. *Image and Vision Computing*, *27*(6), 803-816. https://doi.org/10.1016/j.imavis.2008.08.005

Sheehan, P. W. (1967). A shortened form of Betts' questionnaire upon mental imagery. *Journal of Clinical Psychology*, *23*(3), 386-389. https://doi.org/10.1002/1097-4679(196707)23:3<386::AID-JCLP2270230328>3.0.CO;2-S

Shegokar, P., & Sircar, P. (2016). Continuous Wavelet Transform based Speech Emotion Recognition, (720).

Shen, L. L., Bai, L., & Fairhurst, M. (2007). Gabor wavelets and General Discriminant Analysis for face identification and verification. *Image and Vision Computing*, *25*(5), 553-563. https://doi.org/10.1016/j.imavis.2006.05.002

Shimmer Discovery in Motion (2017). Shimmer | All products. Retrieved August 16, 2017, from http://www.shimmersensing.com/products/all-products/

Siegrist, J., Starke, D., Chandola, T., Godin, I., Marmot, M., Niedhammer, I., & Peter, R. (2004). The measurement of effort-reward imbalance at work: European comparisons. *Social Science and Medicine*, *58*(8), 1483-1499. https://doi.org/10.1016/S0277-9536(03)00351-4

Sigma. (2016). Statistical Analysis 2 : Pearson Correlation. *Centre for Excellence in Mathematics & Statistic Support*, 1-4. Retrieved from http://www.statstutor.ac.uk/resources/uploaded/coventrycorrelation.pdf

Silmee, P. (n.d.). Silmee Bar type.

Silva, M. L. (2014). THE SKIN , THE GREATEST ORGAN Summary, 3730.

Sim, K., Jang, I., & Park, C. (2007). The Development of Interactive Feature Selection and GA Feature Selection Method for Emotion Recognition. In B. Apolloni, R. J. Howlett, & L. Jain (Eds.), *Database* (pp. 73-81). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-74829-8_10

Simões, A. (1992). Further validation of a Satisfaction with Life Scale (SWLS). *Revista Portuguesa de Pedagogia*, *26*(3), 503-515.

Singh, S., Sharma, V., Jain, K., & Bhall, R. (2015). EDBL-algorithm for detection and analysis of emotion using body language. *Next Generation Computing Technologies (NGCT), 2015 1st International Conference On*, (September), 820-823.

Sinha, R, Lovallo, W. R., & Parsons, O. a. (1992). Cardiovascular differentiation of emotions. *Psychosomatic Medicine*, *54*(4), 422-435. https://doi.org/10.1097/00006842-199207000-00005

Sinha, Rajita. (1996). Multivariate Response Patterning of Fear and Anger. *Cognition & Emotion*, *10*(2), 173-198. https://doi.org/10.1080/026999396380321

Sloan, D. M. (2004). Emotion regulation in action: Emotional reactivity in experiential avoidance. *Behaviour Research and Therapy*, *42*(11), 1257-1270. https://doi.org/10.1016/j.brat.2003.08.006

Smeets, T., Dziobek, I., & Wolf, O. T. (2009). Social cognition under stress: Differential effects of stress-induced cortisol elevations in healthy young men and women. *Hormones and Behavior*, *55*(4), 507-513. https://doi.org/10.1016/j.yhbeh.2009.01.011

Smith, R. P., Argod, J., Pépin, J. L., & Lévy, P. A. (1999). Pulse transit time: an appraisal of potential clinical applications. *Thorax*, *54*(5), 452-457. https://doi.org/10.1136/thx.54.5.452

Smith, S. W. (1997). The z-Transform. *The Scientist and Engineer's Guide to Digital Signal Processing*, 605-630. https://doi.org/http://dx.doi.org/10.1016/B978-0-7506-7444-7/50070-4

Smith, S. W. (2003). The Complex Fourier Transform. In *Digital Signal Processing* (pp. 567-580). https://doi.org/10.1016/B978-0-7506-7444-7/50068-6

Solà i Carós, J. M. (2011). Continuous non-invasive blood pressure estimation, (20093). https://doi.org/10.3929/ethz-a-007273889

Soleymani, M., Asghari-esfeden, S., Pantic, M., & Fu, Y. (2013). Continuous emotion detection using EEG signals and facial expressions. *IEEE Conference on Multimedia and Expo (ICME)*, *231287*(231287), 3-8. https://doi.org/10.1109/ICME.2014.6890301

Sony Inc. Sony Product Detail Page - XCDSX90. Retrieved July 9, 2017, from https://pro.sony.com/bbsc/ssr/cat-camerasindustrial/cat-ciindustrial/product-XCEI30/

Sorvoja, H., & Myllylä, R. (2006). Noninvasive Blood Pressure Measurement Methods. *Molecular and Quantum Acoustics*, *27*, 239-264.

SpaceLabs Healthcare (2008). 90207 / 90217 Ambulatory Blood Pressure Systems. *Spacelabshealthcare.Com*.

Spanier, G. B. (1976). Measuring dyadic adjustment: New scales for assessing the quality of marriage and similar dyads. *Journal of Marriage and the Family*, *38*(1), 15-28. https://doi.org/10.2307/350547

Spielberger, C. D. (2010a). State-Trait Anger Expression Inventory. *The Corsini Encyclopedia of Psychology.* https://doi.org/10.1002/9780470479216.corpsy0942

Spielberger, C. D. (2010b). State-Trait Anger Expression Inventory. In *The Corsini Encyclopedia of Psychology*. Hoboken, NJ, USA: John Wiley & Sons, Inc. https://doi.org/10.1002/9780470479216.corpsy0942

Spielberger, CD. (1983). Manual for the State-Trait Anxiety Inventory (STAI). *Consulting Psychologists Press*, 4-26.

Spielberger, Cd, Gorsuch, R., Lushene, R., & Vagg, P. (1983). *State-Trait Anxiety Inventory (STAI)*. *BiB 2010*. Retrieved from http://www.pol.gu.se/digitalAssets/1307/1307827_bib-2010.pdf#page=182

Špulák, D., Čmejla, R., & Fabián, V. (n.d.). Experiments With Blood Pressure Monitoring, 2-6.

SR Research (2017). The EyeLink 1000 Plus. Retrieved April 22, 2017, from http://www.sr-research.com/eyelink1000plus.html

SR Research Ltd (2013). SR Research - EyeLink II. Retrieved June 12, 2017, from http://www.sr-research.com/eyelinkII.html

Sroykham, W., Promraksa, T., Wongsathikun, J., & Wongsawat, Y. (2015). The red and blue rooms affect to brain activity, cardiovascular activity, emotion and saliva hormone in women. *BMEiCON 2014 - 7th Biomedical Engineering International Conference.* https://doi.org/10.1109/BMEiCON.2014.7017432

Sroykham, W., & Wongsawat, Y. (2013). Effects of LED-backlit computer screen and emotional self-regulation on human melatonin production. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 1704-1707. https://doi.org/10.1109/EMBC.2013.6609847

Steffen, M., & Leonhardt, S. (2008). Non-Contact Monitoring of Heart and Lung Activity by Magnetic Induction Measurement. *Acta Polytechnica*, *48*(3), 71-78. https://doi.org/10.1109/TBCAS.2008.915633

Stephens, C. L., Christie, I. C., & Friedman, B. H. (2010). Autonomic specificity of basic emotions: Evidence from pattern classification and cluster analysis. *Biological Psychology*, *84*(3), 463-473. https://doi.org/10.1016/j.biopsycho.2010.03.014

Sthle, L., & Wold, S. (1989). Analysis of variance (ANOVA). *Chemometrics and Intelligent Laboratory Systems.* https://doi.org/10.1016/0169-7439(89)80095-4

Sugiura, A., Eto, T., Takada, H., & Kinoshita, F. (2016). Cerebral Blood Flow in the Prefrontal Cortex while Reading a Novel on a Tablet Computer and its Effect on Sleep Temporary and remaining changes. *2016 11Th International Conference on Computer Science & Education*, (*Iccse)*, 35-40.

Suryadevara, N. K., Member, S., & Mukhopadhyay, S. C. (2012). Wireless Sensor Network Based Home Monitoring System for Wellness Determination of Elderly. *IEEE Sensor Journal*, *12*(6), 1965-1972. https://doi.org/10.1109/JSEN.2011.2182341

Suzuki, S., Matsui, T., Imuta, H., Uenoyama, M., Yura, H., Ishihara, M., & Kawakami, M. (2008). A novel autonomic activation measurement method for stress monitoring: Non-contact measurement of heart rate variability using a compact microwave radar. *Medical and Biological Engineering and Computing*, *46*(7), 709-714. https://doi.org/10.1007/s11517-007-0298-3

Sztajzel, J. (2004). Heart rate variability: A noninvasive electrocardiographic method to measure the autonomic nervous system. *Swiss Medical Weekly.* https://doi.org/2004/35/smw-10321

Tan, A. (2016). Hilbert-Huang Transform. Retrieved November 4, 2017, from https://www.mathworks.com/matlabcentral/fileexchange/19681-hilbert-huang-transform?requestedDomain=www.mathworks.com

Tarvainen, M. P., Niskanen, J.-P., Lipponen, J. A., Ranta-aho, P. O., & Karjalainen, P. A. (2014). Kubios HRV ? Heart rate variability analysis software. *Computer Methods and Programs in Biomedicine*, *113*(1), 210-220. https://doi.org/10.1016/j.cmpb.2013.07.024

Taylor, G. J., Ryan, D., & Bagby, M. (1985). Toward the Development of a New Self-Report Alexithymia Scale. *Psychotherapy and Psychosomatics*, *44*(4), 191-199. https://doi.org/10.1159/000287912

Taylor, S., Jaques, N., Chen, W., Fedor, S., Sano, A., & Picard, R. (2015). Automatic Identification of Artifacts in Electrodermal Activity Data. *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, 1934-1937. https://doi.org/10.1109/EMBC.2015.7318762

TEA. (2016). Captiv - Skilful and adptable software. Retrieved June 30, 2017, from http://teaergo.com/site/en/products/manufacturers/tea/captiv-software

TEA. (2017). Wireless sensor - GSR.

Terburg, D., Morgan, B., & van Honk, J. (2009). The testosterone-cortisol ratio: A hormonal marker for proneness to social aggression. *International Journal of Law and Psychiatry*, *32*(4), 216-223. https://doi.org/10.1016/j.ijlp.2009.04.008

The Mathworks Inc. (2016). MATLAB - MathWorks. https://doi.org/2016-11-26

Theiler, J. (1990). Estimating fractal dimension. *Journal of the Optical Society of America A*, *7*(6), 1055. https://doi.org/10.1364/JOSAA.7.001055

Thielbar, K. O., Triandafilou, K. M., Fischer, H. C., O'Toole, J. M., Listenberger, M. L., Ochoa, J. M., ... Kamper, D. G. (2016). Benefits of using a voice and EMG-driven actuated glove to support occupational therapy for stroke survivors. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(3), 1-1. https://doi.org/10.1109/TNSRE.2016.2569070

Thomas, P. B. M., Baltru?aitis, T., Robinson, P., & Vivian, A. J. (2016). The Cambridge Face Tracker: Accurate, Low Cost Measurement of Head Posture Using Computer Vision and Face Recognition Software. *Translational Vision Science & Technology*, *5*(5). https://doi.org/10.1167/tvst.5.5.8

Thomée, S., Härenstam, A., & Hagberg, M. (2011). Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults - a prospective cohort study. *BMC Public Health*, *11*(1), 66. https://doi.org/10.1186/1471-2458-11-66

Thought Technology Ltd. (n.d.). BioGraph Infiniti Software Upgrade - T7900UP. Retrieved from http://thoughttechnology.com/index.php/biograph-infiniti-software-upgrade.html

Thought Technology Ltd (2016a). FlexComp System with/ BioGraph Infiniti Software - T7555M. Retrieved July 22, 2017, from http://thoughttechnology.com/index.php/flexcomp-system-with-biograph-infiniti-software-t7555m.html

Thought Technology Ltd. (2016b). *Getting Started with BioGraph*. *thoughttechnology.com*.

Tobii AB. (2015). Tobii Pro TX300 screen-based eye tracker. Retrieved July 9, 2017, from https://www.tobiipro.com/product-listing/tobii-pro-tx300/

Tobii Technology AB. (2015). tobii pro studio. Retrieved June 30, 2017, from https://www.tobiipro.com/product-listing/tobii-pro-studio/

Toruzyme, L. (2001). MP150 Product Sheet. *Biopac Systems*.

Toshiba. (2015). Toshiba SilmeeTM W20/W21. Retrieved May 28, 2017, from https://www.toshiba.co.jp/about/press/2015_08/pr_j1701.htm

Tran, T. Q., Boring, R. L., Dudenhoeffer, D. D., Hallbert, B. P., Keller, M. D., & Anderson, T. M. (2007). Advantages and disadvantages of physiological assessment for next generation control room design. *IEEE Conference on Human Factors and Power Plants*, (1), 259-263. https://doi.org/10.1109/HFPP.2007.4413216

Trans Cranial Technologies Ltd (2012). 10 / 20 System Positioning Manual. Trans Cranial *Technologies,* (1), 20. Retrieved from http://www.trans-cranial.com/local/manuals/10_20_pos_man_v1_0_pdf.pdf%5Cnwww.trans-cranial.com

Turan, C., Lam, K., & He, X. (2015). Facial Expression Recognition with Emotion-Based Feature Fusion, (December), 1-6.

Ugoni, A., & Walker, B. F. (1995). THE t TEST. *COMSIG Review*, *4*(2), 37-40.

University of Coimbra. (n.d.). *WHOQOL-BREF (Portuguese version)*.

Van Der Vloed, G., & Berentsen, J. (2009). Measuring emotional wellbeing with a non-intrusive bed sensor. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5727 LNCS*(PART 2), 908-911. https://doi.org/10.1007/978-3-642-03658-3_108

van Eck, M., Berkhof, H., Nicolson, N., & Sulon, J. (2005). The effects of perceived stress, traits, mood states, and stressful daily events on salivary cortisol. *Psychosomatic Medicine*, *58*(5), 447-458. https://doi.org/10.1097/00006842-199609000-00007

Varghees, V. N., & Ramachandran, K. I. (2016). Two-Channel Heart Sound Segmentation

Framework Using Phonocardiogram and Pulsatile Signals, 305-310.

Vaz Serra, A., Cristina Canavarro, M., Simões, M., Pereira, M., Gameiro, S., João Quartilho, M., ... Paredes, T. (2006). Psychometric Studies of the World Health Organization Quality of Life Assessment Instrument (WHOQOL-Bref) for Portuguese of Portugal. *Clinical Psychiatry*, *27*(271), 41-49.

Vermun, K., Senapaty, M., Sankhla, A., Patnaik, P., & Routray, A. (2013). Gesture-based affective and cognitive states recognition using kinect for effective feedback during E-learning. *Proceedings - 2013 IEEE 5th International Conference on Technology for Education, T4E 2013*, 107-110. https://doi.org/10.1109/T4E.2013.34

Viola, P., & Jones, M. M. J. (2004). Robust Real-Time Face Detection. *International Journal of Computer Vision*, *57*(2), 137-154. https://doi.org/10.1023/B:VISI.0000013087.49260.fb

Virkkunen, M. (1994). CSF Biochemistries, Glucose Metabolism, and Diurnal Activity Rhythms in Alcoholic, Violent Offenders, Fire Setters, and Healthy Volunteers. *Archives of General Psychiatry*, *51*(1), 20. https://doi.org/10.1001/archpsyc.1994.03950010020003

Visser, A. K. D., van Waarde, A., Willemsen, A. T. M., Bosker, F. J., Luiten, P. G. M., den Boer, J. A., ... Dierckx, R. A. J. O. (2011). Measuring serotonin synthesis: from conventional methods to PET tracers and their (pre)clinical implications. *European Journal of Nuclear Medicine and Molecular Imaging*, *38*(3), 576-591. https://doi.org/10.1007/s00259-010-1663-2

von Zerssen, D., Strian, F., & Schwarz, D. (1974). Evaluation of Depressive States, Especially in Longitudinal Studies. In *Pichit P (ed). Psychological Measurements in Psychopharmacology* (pp. 189-202). https://doi.org/10.1159/000395076

Vrana, S R, Cuthbert, B. N., & Lang, P. J. (1986). Fear imagery and text processing. *Psychophysiology.* https://doi.org/10.1111/j.1469-8986.1986.tb00626.x

Vrana, Scott R. (1993). The psychophysiology of disgust: Differentiating negative emotional contexts with facial EMG. *Psychophysiology*, *30*(3), 279-286. https://doi.org/10.1111/j.1469-8986.1993.tb03354.x

Vrije Universiteit (n.d.). Ambulatory Monitoring System. Retrieved July 23, 2017, from http://www.vu-ams.nl/

Vrijkotte, T. G., van Doornen, L. J., & de Geus, E. J. (2000). Effects of work stress on ambulatory blood pressure, heart rate, and heart rate variability. *Hypertension (Dallas, Tex. : 1979)*, *35*(4), 880-886.

W. H. Press, B. P. Flannery, S. A. T. and W. T. V. (n.d.). Linear Correlation. Retrieved October 29, 2017, from https://www.statlect.com/fundamentals-of-probability/linear-correlation

Wagner, J. (2006). AuBT - Augsburg Biosignal Toolbox website. Retrieved July 9, 2017, from https://www.informatik.uni-augsburg.de/lehrstuehle/hcm/projects/tools/aubt/

Wahoo Fitness. (2018). Wahoofitness TICKR heart rate monitors. Retrieved January 28, 2018, from https://eu.wahoofitness.com/devices/heart-rate-monitors

Wakamura, T., & Tokura, H. (2002). Circadian rhythm of rectal temperature in humans under different ambient temperature cycles. *Journal of Thermal Biology*, *27*(5), 439-447. https://doi.org/10.1016/S0306-4565(02)00014-1

Wallston, B. S., Devellis, B. M., & Devellis, R. F. (1983). Social support and physical health.

Health Psychology, *2*(4), 367-391. https://doi.org/10.12987/yale/9780300102185.001.0001

Wang, H., Zhou, L. B., & Ying, Y. (2010). A novel approach for real time eye state detection in fatigue awareness system. *2010 IEEE Conference on Robotics, Automation and Mechatronics, RAM 2010*, 528-532. https://doi.org/10.1109/RAMECH.2010.5513139

Wang, R., Wenyan Jia, Zhi-Hong Mao, Sclabassi, R. J., & Mingui Sun. (2014). Cuff-free Blood Pressure Estimation using Pulse Transit Time and Heart Rate. *12th International Conference on Signal Processing (ICSP)*, 115-118. https://doi.org/10.1109/ICOSP.2014.7014980.Cuff-Free

Ware, J. J., Kosinski, M. M., & Keller, S. S. D. (1996). A 12-Item Short-Form Health Survey: construction of scales and preliminary tests of reliability and validity. *Medical Care*, *34*(3), 220-233. https://doi.org/10.2307/3766749

Wassink, P. (2013). Delft Institute of Positive Design | PrEmo (Product Emotion Measurement Instrument). Retrieved June 2, 2017, from http://studiolab.ide.tudelft.nl/diopd/library/tools/premo-product-emotion-measurement-instrument/

Watson, D, Clark, L. a, & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063-1070. https://doi.org/10.1037/0022-3514.54.6.1063

Watson, David, & Clark, L. A. (1999). The PANAS-X: Manual for the Positive and Negative Affect Schedule - Expanded Form. *Department of Psychological & Brain Sciences Publications*. Retrieved from http://ir.uiowa.edu/psychology_pubs/11

WebMD Drugs & Medications (2017a). Citalopram HBR. Retrieved July 23, 2017, from http://www.webmd.com/drugs/2/drug-1701/citalopram-oral/details

WebMD Drugs & Medications.(2017b). Hydrocortisone Cream With Perineal Applicator. Retrieved July 23, 2017, from http://www.webmd.com/drugs/2/drug-10402-3245/hydrocortisone-topical/hydrocortisone-cream-ointment-rectal/details

Weinfurt, K. P., Bryant, F. B., & Yarnold, P. R. (1994). The factor structure of the Affect Intensity Measure: In search of a measurement model. *Journal of Research in Personality*, *28*(3), 314-331. https://doi.org/10.1006/jrpe.1994.1023

Weiser, M. (1991). The computer for the 21st century. *Scientific American*, 94-100.

Weiser, M., & Brown, J. S. (1996). Designing Calm Technology. *PowerGrid Journal.* https://doi.org/10.1.1.135.9788

Weiss, R. (1974). *The Provisions of Social Relationships*. *Doing Unto Others*. New Jersey: Englewood Cliffs.

Weissler, A. M., Harris, W. S., & Schoenfeld, C. D. (1969). Bedside technics for the evaluation of ventricular function in man. *The American Journal of Cardiology*, *23*(April), 577-583. https://doi.org/10.1016/0002-9149(69)90012-5

Weisstein, E. W. (2017). Root-Mean-Square. Retrieved from http://mathworld.wolfram.com/Root-Mean-Square.html

Wen, D., Jia, P., Lian, Q., Zhou, Y., & Lu, C. (2016). Review of Sparse Representation-Based Classification Methods on EEG Signal Processing for Epilepsy Detection, Brain-Computer

Interface and Cognitive Impairment. *Frontiers in Aging Neuroscience*, *8.* https://doi.org/10.3389/fnagi.2016.00172

Weppner, J., & Lukowicz, P. (2011). Collaborative crowd density estimation with mobile phones. *ACM Conference on Embedded Network Sensor Systems*.

Wickert, M. (n.d.). Chap7: Z-Transform.

Wikia (n.d.). Observer effect | Psychology Wiki | Fandom powered by Wikia. Retrieved November 5, 2016, from http://psychology.wikia.com/wiki/Observer_effect

Wikipedia (n.d.). Effective value. Retrieved November 26, 2017, from https://pt.wikipedia.org/wiki/Valor_eficaz

Willemsen, G. H. M., De Geus, E. J. C., Klaver, C. H. A. M., Van Doornen, L. J. P., & Carroll, D. (1996). Ambulatory monitoring of the impedance cardiogram. *Psychophysiology*, *33*(2), 184-193. https://doi.org/10.1111/j.1469-8986.1996.tb02122.x

Wilson, G. F. (2002). An Analysis of Mental Workload in Pilots During Flight Using Multiple Psychophysiological Measures. *The International Journal of Aviation Psychology*, *12*(1), 3-18. https://doi.org/10.1207/S15327108IJAP1201_2

Winton, W. M., Putnam, L. E., & Krauss, R. M. (1984). Facial and autonomic manifestations of the dimensional structure of emotion. *Journal of Experimental Social Psychology*, *20*(3), 195-216. https://doi.org/10.1016/0022-1031(84)90047-7

Wolfram Alpha (2013). Wolfram|Alpha: Computational Knowledge Engine. Retrieved July 8, 2017, from http://www.wolframalpha.com/

Wright, J., Yang, A. Y. a. Y., Ganesh, A., Sastry, S. S., & Ma, Y. (2009). Robust face recognition via sparse representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *31*(2), 210-227. https://doi.org/10.1109/TPAMI.2008.79

Wu, W. H., Batalin, M. A., Au, L. K., Bui, A. A. T., & Kaiser, W. J. (2007). Context-aware sensing of physiological signals. *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, 5271-5275. https://doi.org/10.1109/IEMBS.2007.4353531

Wu, W. H., Bui, A. A. T., Batalin, M. A., Au, L. K., Binney, J. D., & Kaiser, W. J. (2008). MEDIC: Medical embedded device for individualized care. *Artificial Intelligence in Medicine*, *42*(2), 137-152. https://doi.org/10.1016/j.artmed.2007.11.006

XiaoMi. (n.d.). Mi Band 2 - Mi Global Home. Retrieved September 9, 2018, from https://www.mi.com/en/miband2/

xsens (n.d.). IMU Inertial Measurement Unit - Xsens 3D motion tracking. Retrieved September 10, 2017, from https://www.xsens.com/tags/imu/

Yang, A. C. C. (2006). Poincare Plots: A Mini-Review. *PhysioNet Heart Rate Variability. Techniques, Applications and Future Directions*.

Yang, S., & Bhanu, B. (2011). Facial expression recognition using emotion avatar image. *2011 IEEE International Conference on Automatic Face and Gesture Recognition and Workshops, FG 2011*, 866-871. https://doi.org/10.1109/FG.2011.5771364

Zakrzewski, M., Kolinummi, A., & Vanhala, J. (2006). Contactless and unobtrusive measurement of heart rate in home environment. In *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings* (pp. 2060-2063).

https://doi.org/10.1109/IEMBS.2006.260714

Zenonos, A., Khan, A., Kalogridis, G., Vatsikas, S., Lewis, T., & Sooriyabandara, M. (2016). HealthyOffice: mood recognition at work using smartphones and wearable sensors. *2016 IEEE International Conference on Pervasive Computing and Communication Workshops, PerCom Workshops 2016.* https://doi.org/10.1109/PERCOMW.2016.7457166

Zephyr Technology (2012). BioHarness 3.0 User Manual. *Zephyranywhere.Com*.

Zhai, J., & Barreto, A. (2006). Stress detection in computer users based on digital signal processing of noninvasive physiological variables. *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE*, (Ic), 1355-1358.

Zhang, J., Guo, F., Hong, J., & Zhang, Y. (2013). Human-robot shared control of articulated manipulator. *Proceedings - 2013 IEEE International Symposium on Assembly and Manufacturing, ISAM 2013*, 81-84. https://doi.org/10.1109/ISAM.2013.6643493

Zhang, L., Zhou, W.-D., Chang, P.-C., Liu, J., Yan, Z., Wang, T., & Li, F.-Z. (2012). Kernel Sparse Representation-Based Classifier. *IEEE Transactions on Signal Processing*, *60*(4), 1684-1695. https://doi.org/10.1109/TSP.2011.2179539

Zhang, S., Zhang, C., & Yang, Q. (2010). Data preparation for data mining. *Applied Artificial Intelligence*, *17*, 2003. https://doi.org/10.1080/08839510390219264

Zhang, Z., Girard, J. M., Wu, Y., Zhang, X., Liu, P., Ciftci, U., ... Yin, L. (2016). Multimodal Spontaneous Emotion Corpus for Human Behavior Analysis. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 3438-3446. https://doi.org/10.1109/CVPR.2016.374

Zhao, M., Adib, F., & Katabi, D. (2016). Emotion recognition using wireless signals. *22nd Annual International Conference on Mobile Computing and Netwfile:///Home/Jelena/Downloads/Fneng-07-00021.Pdf Orking, MobiCom 2016*, (CONFCODENUMBER), 95-108. https://doi.org/10.1145/2973750.2973762

Zheng, Z., Yang, F., Tan, W., Jia, J., & Yang, J. (2007). Gabor feature-based face recognition using supervised locality preserving projection. *Signal Processing*, *87*(10), 2473-2483. https://doi.org/10.1016/j.sigpro.2007.03.006

Zucco, C., Calabrese, B., & Cannataro, M. (2017). Sentiment analysis and affective computing for depression monitoring. *Proceedings - 2017 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2017*, *2017-Janua*, 1988-1995. https://doi.org/10.1109/BIBM.2017.8217966

ZUNG, W. W. K. (1965). A Self-Rating Depression Scale. *Archives of General Psychiatry*, *12*(1), 63. https://doi.org/10.1001/archpsyc.1965.01720310065008