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A note on the affective computing systems and machines: a classification and appraisal

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Abstract

Affective computing (AfC) is a continuously growing multidisciplinary field, spanning areas from artificial intelligence, throughout engineering, psychology, education, cognitive science, to sociology. Therefore, many studies have been devoted to the aim of addressing numerous issues, regarding different facets of AfC solutions. However, there is a lack of classification of the AfC systems. This study aims to fill this gap by reviewing and evaluating the state-of-the-art studies in a qualitative manner. In this line of thinking, we put forward a threefold classification that breaks down to desktop and mobile AfC systems, and AfC machines. Moreover, we identified four types of AfC systems, based on the features extracted. In our opinion, the results of this study can serve as a guide for future affect-related research and design, on the one hand, and provide a better understanding on the role of emotions and affect in human-computer interaction, on the other hand.

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Keywords: Affective Computing; Artificial Emotional Intelligence; Classification; System; Machine

1. Introduction

We are living in the area of the artificial intelligence (AI) which has brought on some of the greatest advancements in the history of human kind [44]. Currently, there is a lively discussion not about whether, but to what extent AI will shape our tomorrow [51]. Among many topics discussed [6, 21, 36], recently the question of whether a machine can perceive and respond to a human's body language and emotional state is again a breaking point [8]. Artificial emotional intelligence, commonly known as effective computing, addresses with the issues related to technologies able to measure, simulate, and react to human emotions [54]. The concept of emotion-aware machines has fascinated

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a lot of free thinkers and writers [2], then frightened others who claim that AI deployed carelessly could indelibly cut off human civilization from a good future [42].

The inception and rise of effective computing is an attempt to make technology more human. While more and more research has been devoted to address numerous issues, to the best of our knowledge, there is a void regarding the classification of the affective computing solutions. Therefore, this study aims to fill this gap by evaluating and arranging the information in the field in order to formulate a coherent classification, facilitating the on-going research in the most systematic and effective manner. Moreover, we believe that our contribution will also be useful for the business community by providing interesting reading which can spark creative ideas and profitable initiatives.

The rest of the paper is structured as follows. Section 2 is devoted to the theoretical background and other selected qualitative studies. Afterward, in Section 3 we put forward our classification of the affective computing solutions, followed by its more detailed description with supporting examples. Finally, the Section 4 concludes the paper.

2. Background

Nowadays, affective computing (AfC) is an important field of study in the development of systems that can automatically recognize, model and express emotions [31]. In other words, AfC explores how technology can explore an understanding of human affect [7], and how artificial systems (e.g. robots) can be designed to take advantage of affect to enhance their interaction capabilities with humans [23].

2.1. *Definition of Affective Computing*

Rosalind W. Picard, who is the founder and director of the Affective Computing Research Group at the Massachusetts Institute of Technology, coined the term affective computing as “computing that relates to, arises from, or deliberately influences emotions” [41]. In an interview given twelve years later, she said that “*affective computing was an area of research created to give technology the skills of emotional intelligence. For example, a computer can be taught how to differentiate if the person it is interacting with is bored, agitated, or relaxed*” [34].

Nowadays, one can notice that in general there is an informal agreement on the notion of AfC between researchers worldwide. However, while the former attempts aim at describing and classifying AfC, the latter efforts provide the reasons and goals behind the study of AfC and development of systems fueled by AfC. Table 1 presents the summary in this extent.

Table 1: Summary of the elaborated definitions regarding the term Affective Computing.

Author	**Year**	**Definition**
Picard [41]	1997	computing that relates to, arises from, or deliberately influences emotions.
Tao and Tan [55]	2005	trying to assign computers the human-like capabilities of observation, interpretation and generation of affect features.
Francisco *et al*. [9]	2010	subfield of Computer Science that deals with the representation and processing of emotions.
Sokolova and Fernández-Caballero [53]	2015	an interdisciplinary research field which aims to integrate issues dealing with emotions and computers.
Zhuang *et al*. [62]	2017	calculation of emotion and factors that affect emotions, and aimed at making computers possess the ability to perceive, understand and express emotions.
Politou *et al*. [43]	2017	a subfield of human-computer interaction (HCI) named after the field of psychology in which “affect” is basically a synonym for “emotion”; (...) the study and development of systems and devices that are able to recognize, interpret, process, correlate and simulate human affects.
Yates [59]	2018	the study and development of systems, computational devices, or wearables that can process, interpret, recognize, and detect human affects.

Picard gave rise to a new scientific discipline related to artificial intelligence, drawing on machine learning, psychology and neuroscience in order to detect and classify affective states and human emotions. Since its inception, affective computing has attracted the considerable attention of many researchers, who have also elaborated on its definition, among other issues. Currently, there are several studies that allow researchers to view the “lay of the land” in an affective computing. These systematic reviews have identified, evaluated, and synthesized research results, and reliably provided a summary of the state-of-the-art in the AfC domain. In this regard, the next section is an attempt to analyze selected studies to formulate a brief overview of theoretical foundations and methodological achievements in the affective computing domain.

2.2. Systematic Literature Reviews on AfC

Wu *et al*. [57] found that affective computing has been investigated in different domains including engineering, language & art, the social sciences and computer science. Typically, two or more physiological sensors, observed and gathered from the face, hands, body, eyes, voice and mouth, as well as ones collected from physiological signals (such as electroencephalography (EEG), skin conductance response (SCR), oxygen saturation (SpO2) and electrocardiogram (ECG)), were simultaneously applied in order to enrich the flexibility of affective recognition in educational issues. The top ten most widely used statuses in measuring a learner’s emotion were: happy, surprise, neutral, boredom, sad, angry, fear, frustration, disgust and interest. Moreover, the authors paid attention to the issue of the integration of the detected states from various physiological signals caused by the different sampling rates in the case of multimodal emotion recognition systems.

Fuentes *et al*. [10] claim that the majority of studies were focused on automatically detecting user emotions through the means of observation or physiological signals, while few were devoted to the interfaces designed for the self-reporting of emotional states by a user. Another interesting conclusion concerns the user’s privacy since emotional information is sensitive, and thus more research is needed with regard to its management and protection.

Pestana *et al*. [40] point out that there has been a significant rate of growth of AfC research output. The top ten countries of the authors’ affiliation were: the USA, China, England, Germany, the Netherlands, Italy, Spain, Japan, France and Canada. Moreover, the authors conclude that before 2006, AfC research was related to performance and pattern recognition. Next, between 2007 and 2011, the research stream was aimed at signal processing and affect detection. Eventually, after 2011, there was a shift to new applications, including sentiment analysis and meta-analysis, and most notably, to the use of multimodal signals in order to effectively detect and classify human emotional states.

Yadegaridehkordi *et al*. [58] report that there was an increased number and importance of AfC studies in the education domain in the time period from 2010 to 2017. In general, the research goals were focused on the design and development of emotion recognition and expression systems, as well as single methods and instruments, with the aim of examining the relationships among users’ motivation, learning style, cognition, and emotional state. The most widely used affective measurement instruments were:

- **textual channel**, concerns a self-reporting method in which a user fills in a questionnaire; alternatively a text typed by a user is collected and analyzed to detect his or her current emotional state; thirdly, an expert observation is utilized and carried out by a professional with specific expertise in an area of study;
- **visual channel**, relates to the three natural and observable methods, namely facial expression, head pose, as well as body gesture;
- **vocal channel**, by design accurate and discernible, these methods are: speech, prosody (acoustic properties beyond those of consonants and vowels, including variables such as duration, intensity, pitch, voice quality and spectral properties [47]) and intonation (variation in the pitch of the voice);
- **physiological channel**, concerns a family of measurement methods such as electroencephalogram (EEG), eye gaze tracking (EGT), electrocardiography (ECG), heart rate (HR) & heart rate variability (HRV), blood volume pressure (BVP) and skin conductance level (SCL);
- **multimodal channels**, a combination of the aforementioned channels, applied together to overcome the constraints of particular channels, and to improve total measurement accuracy.

To sum up, the Authors also argue that the integration of textual and visual channels was the most widely used multimodal channel in AfC studies. Moreover, dimensional theories and models were the most preferred models, since they include a wide range of emotional states. The following ten most frequent emotion states were considered and studied: boredom, anger, anxiety, enjoyment, surprise, sadness, frustration, pride, hopefulness, and hopelessness.

According to Aranha *et al*. [1], the most frequent application areas in the studies concern:

- Education: 22 percent,
- Health: 10 percent,
- Arts: 9 percent,
- Security: 3 percent,
- No application: 55 percent.

Also, regarding the application areas of the studies, especially in the Education area, there is a predominance of software defined as games. This fact shows that the use of AfC has received special attention by developers of digital education games, an activity that tends to benefit from personalization according to the students' profile and their state of emotions. According to Tomkins' Affect Theory [56], human emotions can be dichotomously categorized into discrete, or continuous (or dimensional) emotions. While the former category spans a plethora of labels (e.g. happiness, sadness, anger, fear, surprise, disgust and neutral), the former category typically imposes three states, namely: positive, negative or neutral. Moreover, in most studies (71%), emotions were modeled in the continuous way, 16% used discrete models, and 10% did not indicate the model of emotion adopted.

Guo *et al*. [16] performed a bibliometric analysis of affective computing studies published during the period from 1999 to 2018. Considering the authors' findings on the AfC research, one can identify its three development stages. In the first, a single sensing modality was utilized for affect measurement such as face video, galvanic skin response (GSR), or EEG or ECG signals. In the second stage, fostered by new technologies, the research mainstream utilized multimodal contents, regarding video, audio, and text, but also biosensors (e.g. GSR, EEG, etc.). Eventually, in the third, facilitated by high-performance computing (HPC), machine learning techniques have been applied and evaluated in comparison with other methods. In this stage, considerable attention and application concerned:

- **deep learning approach**, artificial neural networks (ANNs) in which multiple layers of processing are used to extract progressively higher level features from the data,
- **sentiment analysis**, computationally identifying and categorizing opinions expressed in order to determine the user's attitude towards a particular topic, and
- **emotion categorization**, computational techniques that are able to distinguish or contrast one emotion from another.

Mejbri *et al*. [32] argue that the majority of studies about emotion recognition use unimodal systems in which emotion detection based on facial expressions is the most common. The major research purpose is designing/building systems, approaches, methods, detectors for emotion recognition. For the e-learning environments, conversational agents are the most common. The emotions detected or used are basic emotions, non-basic emotions, learning-centered emotions, trait emotions, or a combination of two or three of them. This systematic literature review also provides the major findings, challenges, and future research.

In the context of the automatic emotion recognition in children with autism, Landowska *et al*. [26] identified three basic emotions that were the most frequently recognized, namely: happiness, fear, and sadness. Moreover, the authors claim that both single-channel and multi-channel approaches were applied, with a preference for the first one. For multimodal recognition, early fusion was the most frequently applied, while machine learning methods, support vector machines (SVM) and ANNs were the most popular methods used to develop emotion recognition classifiers.

Below, Table 2 presents a brief summary of the identified and above-discussed qualitative studies.

3. Affective Computing Systems and Machines

From the inception of the first affective computing system to this day, all of these artificial systems have relied on both modern computer hardware equipment and specialized software applications. Therefore, henceforth, the notion of the system will cover both hardware and software technologies which work together. Now, if the portability criterion is taken into account, there are two generations of computing systems: (1) desktop and (2) mobile. While the former is

Table 2: Summary of the selected systematic literature reviews devoted to different aspects of AfC research.

Author	**Year**	**Research Topic**
Wu *et al.* [57]	2016	Education/ learning
Fuentes *et al.* [10]	2017	Trends in the area of interfaces for the self-report (subjective) of emotions
Pestana *et al.* [40]	2018	AfC evolution and collaboration patterns in the period 1997–2017
Yadegaridehkordi *et al.* [58]	2019	Education / learning
Aranha *et al.* [1]	2019	Computer applications
Guo *et al.* [16]	2020	AfC in general
Mejbri *et al.* [32]	2021	E-learning environments
Landowska *et al.* [26]	2022	Automatic Emotion Recognition in Children with Autism

related to computing devices which are generally designed to remain in a fixed location, the latter concerns portable-computing devices such as smartphones and tablets, as well as wearable bracelets and watches [14].

Moreover, recent advancements in robotics over the past decade have involved the development of robotic machines capable of interacting and communicating with a human in a dialogue, reasoning from both spoken text and the current emotional state of its interlocutor. Eventually, having said that, considering both systems and machines, we have distinguished three generations of affective computing models:

- 1st generation: desktop affective computing systems.
- 2nd generation: mobile affective computing systems.
- 3rd generation: autonomous and affective computing robots.

It should be noted here that, while either a desktop or a mobile system is intentionally and consciously operated by a human operator, commonly defined as a user, a robot is autonomous by design, which means it operates without explicit user control.

Thinking in the terms of the process-based approach [4], AfC systems rely on a sequence of three separate, deliberate and systematic processes [61]:

1. Data collection.
2. Affect recognition.
3. Affect expression.

Taking into account the context of the subject matter, data collection is the process of gathering and measuring data on affective variables by using one or more input devices (modalities). Typically, hardware equipment is used such as: digital cameras [18], microphones [3], motion sensing devices [29], as well as data collectors connected to the central or peripheral nervous systems [48].

Affect recognition is the process that aims to detect and classify emotions by analyzing collected input data [38]. To this end, numerous methods and techniques can be used (e.g. K-Nearest Neighbor [20], Support Vector Machines [30], naive Bayes [45]), whereas the latest studies have focused on the fusion of the multimodal techniques [39]. Here, it should be noted that the modality is the way or manner in which an individual's emotions are expressed (e.g. facial expression, body gesture, hear rate, muscle tension [26]).

Affect expression is a system output expressed through a combination of nonverbal or/ and verbal communication channels [22], in relation to the recognized emotional state of the individual. The nonverbal communication types include body gestures, eye contact, eye gaze, facial expressions, paralanguage (e.g., loudness or tone of voice, rate, pitch), while the verbal communication is the use of words to convey a spoken message.

Now, if one considers the above-described process on the one hand, as well as the state-of-the-art affective computing systems on the other, it is possible to point out four types of AfC systems. Table 3 below presents a summary.

The above classification should be read as follows. Type I applies to those AfC systems which are designed with the aim of collecting affective data only. Analogously, type II includes the AfC systems that have the capability of processing affective data as an input, and classifying the emotional state, returned as an output. If an AfC system

Table 3: Features and types of affective computing models.

Feature	**Type** I	II	III	IV
Affective Data Collector	•		•	•
Affect Recognition		•	•	•
Affect Expression				•

has features of the former two types, then it is a system of type III. Finally, if a system functionality covers all three features, it is a system of type IV.

3.1. 1st Generation: Desktop AfC Systems

Considering type I (data collectors) of the first generation of affective computing systems, desktop solutions comprising four central modalities such as [55]: speech, facial, body gestures and movement, signals from the central or peripheral nervous system, as well as their combinations of two or more, used either simultaneously or alternately, are defined as multimodal systems. In the case of speech, any voice recording software that is able to capture the vibrations produced by a speaker, and able to translate those vibrations into electrical signals is typically used. Analogously, facial data is collected by digital cameras in the form of a set of images, or as video footage, which is also used as a record of body gestures and movement [15]. Eventually, signals from the peripheral or/ and central nervous system are gathered via electronic devices by sensors attached to particular parts of the human body. Optionally, type I AfC systems offer the capability of supporting manual labelling and annotations.

Type II AfC desktop systems have been designed and implemented with the aim of affect recognition from input data prepared and shared by other researchers. Thus, by nature the contributions of such studies usually concern the development of relevant modifications regarding the existing techniques or, more rarely, introducing a new ones. Until now, considering the bulk of the contemporary literature, the research mainstream has been focused around the issue of improving performance of affect recognition.

Last but not least, type III AfC systems both collect and process affective data, and therefore are relatively more time-consuming and laborious to organize. Indeed, the design and elaboration of affective datasets requires considerable effort due to the "definition of representative behaviors, and the choice of expressive modalities, and ultimately the collection and labeling of large amount of data" [15].

It should be noted here that there are advanced multi-sensory display systems (e.g. Virtual Reality headsets and motion tracking devices) which support elicitation and detection of human emotions. For instance, Sansar, a virtual world, can be described as a screen-based simulation, or a metaverse, a collective virtual shared space that users can access via VR reality headsets, VR body trackers, PCs and mobile phones [13]. Moreover, recent studies show that virtual reality video games are capable of eliciting positive emotions, as well as downsizing the negative emotions and state anxiety of their players [37]. To summarize, type IV AfC systems let users share their emotions not only with others, but also with their emotionally aware digital equivalents.

3.2. 2nd Generation: Mobile AfC Systems

Type I mobile affective computing systems encompass both mobile devices and mobile applications, which together enable the collection of affective data. To this end, Table 4 presents identified solutions.

In the case of the type II, we have identified only one mobile AfC system, presented by Guo *et al*. [17]. Here, the authors considered a solution dedicated to real-time facial expression recognition. The input data concerns AffectNet [33], the largest database in the field of facial affective computing. The classification task takes advantage of the Deep Learning Approach in the form of Convolutional Neural Networks (CNN).

Eventually, we were also able to identify three mobile solutions that falls into the type III category, but none have been elaborated so far that fit into type IV. Hence, Table 5 provides an overview only of the former type.

To sum up, it seems rational to conclude that one might expect more mobile solutions.

Table 4: Type I mobile AfC systems.

Name	Goal	Data Source (Channel)
iHEARu-PLAY [19]	Data collection and multi-label annotation of multi-modal affective speech databases based multiplayer games	single-select questions. Multiple-select questions
BandReader [25]	Data Acquisition from Wearable Devices	Wristbands (e.g. Apple Watch 3, Empatica E4, Microsoft Band 2, Scosche Rhythm+, Xiaomi Mi Band 2)

Table 5: Type III mobile AfC systems.

Name	Goal	Data Source (Channel)	Method
emoCook [11]	Adapting the pace and difficulty level of an educational game	Camera, audio speech, keylogging	Multimodal emotion detection
No-name [50]	Stress recognition	Pre-surveys, wearable sensor, three-axis accelerometer data (ACC), skin conductance (SC), mobile phone usage data (call, SMS, location and screen on/off), surveys (morning, evening), post-experiment survey	Correlation analysis. Machine learning
WellAff [49]	Recognize affective states for wellbeing support	Wearables (smartwatches, wristbands, i.e., Empatica E4 and Samsung Galaxy Watch 2019); EMA-type questionnaire	Binary classifier

3.3. 3rd generation: AfC Machines

The third generation of Affective Computing concerns advanced machines, namely affective social robots. Here, the prominent example of the Type III system is Sophia (see Figure 1), the first “social robot” that can mimic social behavior and induce feelings in humans.

Fig. 1: Affective social robot, meet Sophia, an example of an AfC type III system. Front (left) and back views (right). Source: https://robots.ieee.org/robots/sophia/

Sophia is an invention of David Hanson, an American roboticist, the founder and Chief Executive Officer of Hanson Robotics, a Hong Kong-based robotics company founded in 2013. Sophia was activated on February 14, 2016 and made her first public appearance in March 2016 at South By (SXSW) in Austin (Texas, USA). Her performance showed that she spoke affectionately, intelligently, emphatically, and eventually softly [60].

Another example of a social humanoid robot able of recognizing faces and basic human emotions is Pepper (see Figure 2), manufactured by SoftBank Robotics, introduced in June 2014 and put on the market in December 2015 [52]. Pepper communicates with people through conversations and his touch screen. It makes use of numerous sensors, 2D and 3D cameras, microphones and sonars for omnidirectional and autonomous navigation, and for multimodal interactions. Moreover, it implements speech recognition in 15 languages for making conversations with humans. Pepper is based on an open and fully programmable (using Python SDK) platform, NAOqi 2.5 [46].

Fig. 2: Pepper, an autonomous semi-humanoid programmable robot, designed with the ability to read emotions. Source: https://www.softbankrobotics.com/emea/en/pepper

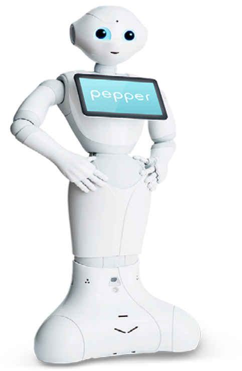

Fig. 3: Buddy, a social robot for the senior, healthcare, education and hospitality markets. Source: https://buddytherobot.com/en/buddy-pro/

More than 2,000 companies use Pepper as an assistant (or receptionist) to welcome, inform and guide visitors in an innovative way. Applications of the robot can be found in banks, medical facilities, restaurants, airports and households. Schools, colleagues and universities use it to conduct research into human-robot interactions. In June 2021, after assembling 27,000 units, due to diminishing demand [35] SoftBank paused production of the robot.

A different approach to utilizing Affective Computing in social robotics is Buddy (see Figure 3), a robot created by Blue Frog Robotics [5]. It aims to drive significant positive impact on major social issues: education, inclusion of vulnerable people and aging population. Buddy is 56 cm tall, utilizes 2D and 3D cameras, numerous sensors and an 8" touch screen display to interact with users. It provides an open and scalable platform with a dedicated SDK for programmers (Android), making it a good tool for custom solutions. The main areas where the robot is used and where it fills a gap is as an educational companion (learning while having fun for children), senior companion (mostly for seniors living alone at home) and partnering with the most vulnerable children (encouraging the inclusion of a student who is unable to attend classes, allowing him/her to take distance courses) and for children with disabilities (emotional and behavioral disorders and autism spectrum).

4. Conclusions

This study is an attempt to arrange existing affective computing solutions into categories (hereafter generations) according to shared qualities. For this purpose, we put forward a threefold classification. The first generation is affective computing desktop systems including both hardware, software and peripheral equipment. The second generation, related to the former, concerns mobile affective computing solutions. Ultimately, the third generation, drawing on artificial intelligence, robotics and mechatronics, covers the most advanced and innovative technologies, namely autonomous robots, which physically embodies, interacts and communicates with humans by following social behaviors and rules.

Undoubtedly, AfC has brought considerable attention to research, becoming more relevant today due to big data, machine learning and advanced robotics. Nevertheless, affective computing is the study of a human factor to leverage human-computer interaction at the next level. Moreover, recent studies were devoted to understanding a learner's affect throughout the learning process [28], and more specifically the impact of motivation on knowledge and skills acquisition [12]. On the other hand, the application of AfC can bring tangible benefits for businesses by learning the emotional states of clients, employees and stakeholders, and in this way effectively working toward meeting their unspoken expectations. An example is Emotion Aware Recommender Systems (EARS), which plays a major role among affective computing solutions [27], where the recognized user emotions and identified customer communities foster selling, upselling and upgrading products and services [24] by integrating and processing explicit and implicit data from social media, wearables and smartphones.

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