Article:
Luneski, Andrej, Konstantinidis, Evdokimos and Bamidis, Panagiotis (2010) Affective Medicine: a review of Affective Computing efforts in Medical Informatics. Methods of Information in Medicine, 49 (3). pp. 207-218. ISSN: 0026-1270

https://doi.org/10.3414/ME0617

Affective Medicine: a review of Affective Computing efforts in Medical Informatics

A. Luneski[1,2] , E. Konstantinidis[1], P.D. Bamidis[1, *]
[1]Lab of Medical Informatics, Medical School, Aristotle University of Thessaloniki, Greece
[2]South-East European Research Centre (SEERC), Thessaloniki, Greece

[*]Corresponding author

Andrej Luneski
SEERC - South East European Research Centre
17 Mitropoleos Str, 54624 Thessaloniki, Greece
Tel: +(30) 2310 253 477 (221)
Fax: +(30) 2310 253 478
Email: anluneski@seerc.org

Evdokimos Konstantinidis,
Lab of Medical Informatics
Medical School
Aristotle University of Thessaloniki
email: evdokimos@gmail.com

Panagiotis D. Bamidis,
Lab of Medical Informatics
Medical School
Aristotle University of Thessaloniki
PO Box 323, 54124, Thessaloniki, Greece
tel: +30-2310-999310/999332
fax: +30-2310-999263
email: bamidis@med.auth.gr

This article is not an exact copy of the original published article in Methods of Information in Medicine. The definitive publisher-authenticated version of "A. Luneski, E. K., P.D. Bamidis. (2010). Affective Medicine: a review of Affective Computing efforts in Medical Informatics. MIM, 49(3), 207–218" is available online at: http://www.schattauer.de/en/magazine/subject-areas/journals-a-z/methods/issue/special/manuscript/12987/show.html

Summary

Background: Affective computing (AC) is concerned with emotional interactions performed with and through computers. It is defined as "computing that relates to, arises from, or deliberately influences emotions". AC enables investigation and understanding of the relation between human emotions and health as well as application of assistive and useful technologies in the medical domain. Objectives: 1) To review the general state of the art in AC and its applications in medicine, and 2) to establish synergies between the research communities of AC and medical informatics. Methods: Aspects related to the human affective state as a determinant of the human health are discussed, coupled with an illustration of significant AC research and related literature output. Moreover, affective communication channels are described and their range of application fields is explored through illustrative examples. Results: The presented conferences, European research projects and research publications illustrate the recent increase of interest in the AC area by the medical community. Tele-home healthcare, AmI, ubiquitous monitoring, e-learning and virtual communities with emotionally expressive characters for elderly or impaired people are few areas where the potential of AC has been realized and applications have emerged. Conclusions: A number of gaps can potentially be overcome through the synergy of AC and medical informatics. The application of AC technologies parallels the advancement of the existing state of the art and the introduction of new methods. The amount of work and projects reviewed in this paper witness an ambitious and optimistic synergetic future of the Affective Medicine field.

Keywords

Affective computing, emotions, health, medicine, human-computer interaction, learning, autism, biosensor networks.

1. Introduction

More than a decade has passed since the publication of the Affective Computing book by Picard (1), in which Affective Computing (AC), i.e., "computing that relates to, arises from, or deliberately influences emotions", was first considered as a significant emerging area with enormous research potential and a wide spectrum of prospective applications. With its interdisciplinary nature, AC seeks to provide a complete and reliable research base on which to ground research into the link between emotions and computers through the use of theoretical descriptions of human affective states as well as their influence on social, cognitive, physical or other levels of human actions. In addition, AC is concerned with practical applications of computer technologies to achieve potentially a positive impact on human everyday lives by monitoring, communicating or changing the affective states of people.

Perhaps one of the most significant research domains of AC is directed towards the relation between emotions and human health, both mental and physical. It can be argued that the three main motivations for AC research are:

a) The interrelation among emotions and health. More specifically, it is well known that emotions and health are tightly connected (2). This connection has been studied and reported by medicals doctors, psychologists, philosophers, and more recently, even by computer scientists and engineers.

b) The growing use of computers in the modern societies and their impact on all facets of human lives. In everyday interaction with computers, people exhibit emotions that in certain contexts might influence their health (1).

c) The availability and constant development of technologies that can facilitate the application of AC in the medical realm. The existing software systems and hardware sensors can be used in the process of monitoring, recognition, as well as expression of emotions for various medical purposes (3).

This paper attempts to examine and discuss each of the above reasons that have lead or are leading to the emergence of what Picard named the "affective medicine" domain (3). A detailed review of the state of the art in the field of AC from the Medical Informatics (MI) perspective is provided. The review outlines the motivation, underlying principles, methods and potential benefits of research in affective medicine. However, the great interdisciplinarity and wide application spectrum of AC precludes a comprehensive coverage. Consequently, we restrict the scope of the review to what we identify as the most significant and influential research efforts, focusing on areas in which we believe AC has significant potential for enhancing the effectiveness of MI. These are identified by reviewing the evolution of European research fund calls and work carried out by pioneers in related fields. Additionally, we discuss challenges relating to the creation of useful synergies between AC and MI which potentially will lead to development and further improvements of emotionally-aware systems for health applications.

The structure of the review is as follows. Section 2 examines previous attempts at reviewing the application of AC in MI. In section 3, issues related to determinants of the human affective state and their corresponding health effects are discussed, coupled with an illustration of affective computing research (literature) output. This section, together with the above-mentioned reasons under a), b) and c), establish the significance of and the need for application of AC in MI, and hence the motivation for research in this area. Section 4 describes communication channels in human emotions with and through computers, by examining the existing relevant technologies and originating application fields. These are further elaborated in section 5 to establish synergies with the MI research domain. The final section contains a concluding discussion.

2. Related work

In the short time period since the AC area was introduced, a significant number of research efforts have attempted to identify the main challenges and application areas. Initially, the use of computers for achieving awareness of emotional states of people was mainly thought to impact on the basic nature of human-computer interaction. However, subsequently this has emerged as an issue in other application areas, such as, medical/health informatics, learning, games, social computing, etc. (1).

Shortly after the publication of the Affective Computing book, researchers started discussing the potentials of AC in MI. One of the earliest works, by Webster (4), outlined various possibilities for synergies between the research agendas of AC and MI. Specifically, these were identified "…from advisory systems that understand emotional attitudes toward medical outcomes, to wearable computers that compensate for communication disability, to computer simulations of emotions and their disorders…" (4). In addition, the research results of psychologists, neurologists and psychiatrists on emotions could potentially benefit adaptive intelligent systems, which "will increasingly rely on emotions to compensate for their own conflicting goals and limited resources" (4).

Smith and Frawley (5) gave their own view on how research on emotions can be applied in medicine. They focused on two scenarios: 1) emotional user interfaces in virtual environments for health care professionals and patients, and 2) emotions in computer as support for psychiatry. Among the potential applications listed in (5), were: enhancing physicians' empathy via interaction with a virtual patient, reacting emotionally to a virtual patient's response to physician-caused pain, such as in touching a simulated burn victim, simulating a world in a disabled person to enhance social involvement so they do not become depressed, etc.

Later, Picard introduced the term "affective medicine" (3), highlighting research at the MIT Media lab towards emotionally aware and emotionally responsive computers, specifically targeted at certain categories of emotions closely related to health. As stated in (3), the principal aim is to enable computers to recognise some of the most frequent emotions that people experience while interacting with today's technology, such as frustration, irritation or stress. The computers can afterwards facilitate the improvement of human computer interaction and decrease the level of stress or related negative emotions. The focus on these specific emotions is based on the statistical analysis for health concerns, which found stress to be at the top of the list, along with cancer, AIDS, hypertension or other major health conditions.

Predinger and Ishizuka (6) followed a more specific approach, motivating the use of AC and avatar technologies for tele-home health care. They presented the state-of-the art in the process of measuring physiological data of a user in real-time, interpreting them as emotions, and addressing the user's affective states in the form of empathic feedback through life-like characters.

It might be assumed that the absence of review studies on what is considered to represent affective medicine is due to the immaturity of AC. Although the potential of AC in healthcare has already been established in pilot projects, the adoption of its methods and technologies has started only recently. Therefore, we believe that at this

stage in the development of affective medicine, it is crucial to examine the most significant research efforts, motivations and methodological approaches in this young and rapidly evolving field.
The work in the AC field is generally concerned with monitoring and recognition of emotions, and the development of technologies that can potentially influence emotional states by acting emotionally. The latter is highly dependent on knowledge about emotions as determinants of human everyday actions. In the medical field the application of AC technologies can benefit from the awareness of the role that emotions play in all aspects related to human health. This can lead to discovering significant potentials and motivations for synergies between AC and medical informatics.

3. The Human Affective State as a Determinant of Health

The strong relationship between emotions and human health has been recognized as early as the ancient times. Ancient Greek philosophers and scientists, such as Socrates and Hippocrates, considered emotions as determinants of human health and diseases (2). Emotions have been mentioned in religious writings: “The joyfulness of man prolonged his days”, (Bible, Ecclesiasticus.30:22). Nowadays, the dynamic lifestyle leads to more unpleasant and stressful situations, accompanied by frustration, irritation, depression and other emotions that can have a negative impact on human health. Thus, a significant motivation exists for researching emotions and their impact on specific aspects of human health. Emotional state, along with provision of physical security, can lead to health benefits (7), while helplessness and negative emotions, such as stress or depression, have been associated with a weakened human immune system (8; 9). Cohen (9) showed that people in depressive conditions and with poor social connections have a four times higher risk of suffering from a common cold. Continuous stress can also increase the risk for myocardial ischemia (10). Coping with negative emotions is enabled by the organism’s defence mechanisms (11). Since stressful emotions can have an impact on one’s mental health, adaptivity of defence mechanisms can protect an individual from their negative effect on health (12).
On the other hand, positive emotions contribute considerably to physical and mental health. Both mental and physical health are influenced by self-esteem and self-efficacy (13). For example, optimistic feelings have accelerated the recovery pace of patients undergoing heart surgery or having breast cancer (14). Additionally, optimism can help in stressful situations and can prolong life by increasing the positive “self-view” and happiness (15). Maintaining a positive mood in stressful situations increases the level of salivary immunoglobulin (S-IgA), which is known to have a protective effect against respiratory diseases (16). Stress is decreased by humour and laughter, affective expressions that help in preserving a positive mood and strengthen the immune system. Positive emotions can also act as a medicine for cardiovascular diseases. Middleton and Byrd (17) state that elderly patients suffering from cardiovascular diseases had a lower number of readmissions to hospitals when they were overall happier than others
Recent findings oppose the generally accepted view that health only benefits from positive emotions, moods or related affective states. Martin et al. (18) show that cheerfulness in young children can potentially lead to shorter lifespan. The term cheerfulness encapsulates both the sense of humour and optimism. Even though

cheerfulness has not been listed as the main cause for shorter lives, it is arguably connected to harmful lifestyles (e.g., smoking or drinking).
Finally, the processing of emotional information (real as in fear or anticipated as in anxiety) regulates the allocation of attention, but may also divert resources away from attention performance, particularly for those showing elevated anxiety. This adaptive behaviour can often become maladaptive and lead to disorders that relate to elevated anxiety. External events, particularly those that threaten an individual (stress), also result in elevated glucocorticoid levels, which may persist in situations of chronically threatening social adversity and become dysfunctional (19; 20; 21).
This notion indicates a whole range of applications, where AC is already contributing (as described above). However, it also opens up a large potential synergetic research space for medical informatics (with bio-informatics included; see section below), in order for the actual and currently largely unknown pathomechanisms of fear and anxiety to be revealed.

4. Affective communication

The human affective state is expressed and communicated through various channels: text (contextual information), audio (speech), face expressions and body gestures (visual) and internal physiological changes (blood pressure, heart beat rate, respiration, skin sweating etc.). Communication is realised through multimodal sensing and expressing of affect, i.e., fusion of the different modalities into one emotion carrier channel (Figure 1).

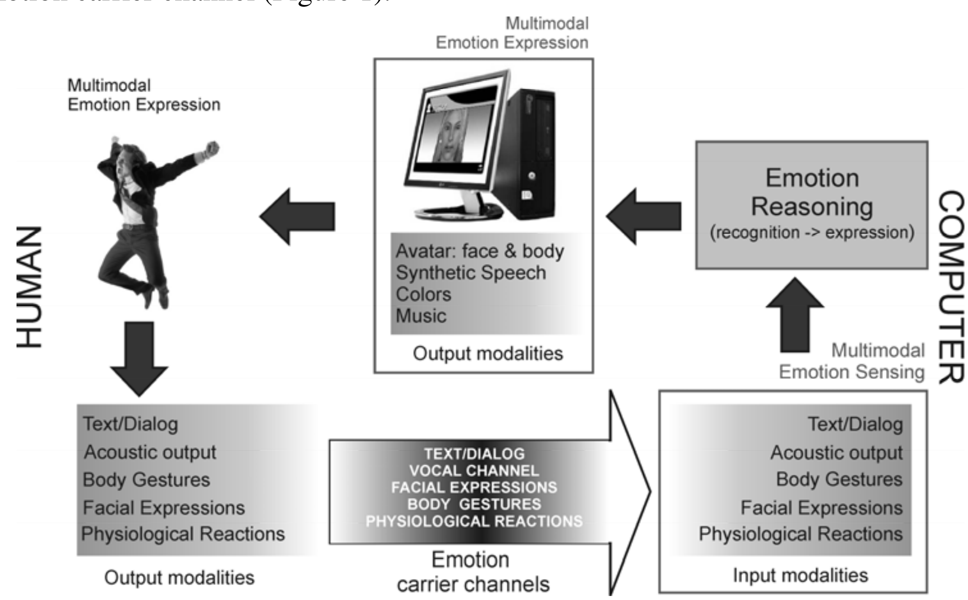


Figure 1. Affective multimodal Human Computer Interaction

User monitoring is necessary if computers are to be applied to identify human emotional states. Specifically, the data collected from the user must to be analyzed to classify and recognise the current emotional state. Humans tend to communicate emotions through a combination of speech, facial expression, hand gestures, etc., and it is generally accepted that human-like expression of emotions is a complex and multi-modal process. Furthermore, the individual modalities have their own characteristics and require specific methods for emotion recognition or expression. Due to the complexity of expressing emotions, however, each mode or channel for expressing emotion has been addressed separately and tackled by different research communities.

4.1. Speech

Affective speech is expressed through semantics and speech prosody. While semantics (what has been said) is a more obvious way of identifying one's emotional state, since prosody can provide more detailed information. The term prosody combines nonsemantic cues in spoken language, such as: fundamental frequency (pitch), rhythm, loudness, intonation, formant structure of speech sounds etc. Research efforts in AC can be mainly divided into recognition and synthesis of emotions in speech.

Experiments in recognizing emotions from speech generally follow similar steps: emotions elicitation, feature selection and recognition by use of classification patterns. However, the methods employed in each step may vary. The elicitation methods or the selection of the speech corpora has the most significant impact on the recognition results. Acted speech is the most frequent data set for emotion recognition (30-32). Actors are presented with various situations into which they need to imagine themselves, and to speak predefined sentences in one or more specified emotions. However, recordings from actors generally carry the information of how emotions should sound, rather than how they actually appear in natural conversations. Therefore, recent efforts have focused on recognizing emotions from natural speech recordings (33; 34).

The majority of experiments, (e.g., (30; 31; 34)) have attempted to recognize the "basic six" emotions – anger, sadness, joy, fear, disgust and surprise, with addition of happiness, neutral, and boredom, among others. The average success rate is between 70% and 80%, which is higher than the human recognition rate of around 60%. In (35), the same success rate was achieved for only approval and disapproval, while others (31) have exceeded 90% success for anger.

Emotional speech synthesis is performed using formant and concatenative synthesis methods. While formant synthesis provides more flexibility in the text-to-speech conversion, it also results in an unnatural robotic sound (36-38). On the other hand, though concatenative synthesis methods are more complex, the output is much more natural and closer to human-like speech (39; 40).

Research in affective speech has provided significant benefits in many medical domains. The most characteristic manifestations of Williams Syndrome are low non-verbal intelligence quotient, impairments in planning and problem solving, uneven cognitive profile linguistic disabilities, etc. (41). When examining the affective vocal prosody in a story telling experiment among children, adolescents with Williams Syndrome used more affective expressive prosody than normally developing children. Affective prosody provides significant insights for people suffering from Asperger Syndrome. Despite normal early language development, individuals with Asperger Syndrome are often characterized by abnormal prosody and impaired semantics and pragmatics, as well as poor social skills and emotional behaviour (42). Additional studies in patients with Parkinson Disease found that these patients fail to recognize emotional content in prosody (43).

4.2. Facial expressions

Facial expressions and body gestures are the most obvious and significant channels for expressing affect, as most human communication is non-verbal. There are certain visually distinctive facial expression characteristics for the “universal” human emotions, such as happiness, anger, sadness, surprise, fear and disgust (44). Each of the basic emotions is characterised by a set of muscular movements, formalised by what is called the Facial Action Coding System (45). The Facial Action Coding System has been widely used for experiments on emotion recognition by the computer, from human facial expressions (e.g. 46; 47). As with emotional speech recognition, experiments for recognising emotions from facial expressions can be grouped into two categories, according to the elicitation methods: acted or deliberately expressed emotions (e.g. (48) and spontaneously expressed emotions in everyday activities, such as casual dialogs, group tasks etc. (49, 50). While part of the experiments have focused on recognizing one or two emotions, such as anger or fear (51, 52), most facial analysis research has used the Facial Action Coding System in an attempt to characterize and thus classify certain emotions (e.g. (53)).

Virtual characters (avatars) are the most common visual human-like appearance of computers and they usually appear as face-only characters (54). Studies have shown that there is no significant difference in emotional expression of people among themselves and towards avatars (55). Emotion expression by avatars has proven to have enormous significance in human-computer interaction (56). Following the nature of the human face, emotional expression by avatars is usually facilitated through distinct facial expressions of the six basic emotions, together with synthetic speech (text-to-speech or pre-recorded speech). Emotions articulated through facial expression of an avatar can be easily distinguished by the users (54). Some of the most characteristic applications are concerned with the ability of computers to respond to user frustration by expressing empathetic emotions through facial expressions of an avatar (57). Emotionally-expressive avatars have also been used in therapies and learning experiments for autistic people (58;59), as well as for investigating the ability of children with disruptive behaviour disorders to identify emotional faces and stories (60).

4.3. Body gestures

Body gestures differ from other movements since they are the only visual stimulus that is experienced in both perceiving and producing emotions (61). The investigation of the affective information carried in bodily movements remains a poorly covered area of research and few experimental results have been published. It has been discovered that there exist multiple body regions which carry emotional information, and can be used for automatic recognition (62). A significant study has been carried out by Bianchi-Bertzone and Kleinsmith (63), in which a model was developed which has the ability to self-organise postural features according to affective states. This is used for human-robot interaction, where robots learn to recognise affective states in humans by interacting with them.

Nearly all research towards capturing emotion-related body movements has used deliberate and guided elicitation of emotions, This is because recognising all the movements in a spontaneous situations is difficult and classifying them into emotional categories is even harder. Reseaerchers have focused on a small set of “basic emotions” (e.g. (64). Some recent studies attempted to remove personal movement bias, which can have a significant benefit for automated affect recognition from body motion, and the usage of non-propositional movement qualities, such as amplitude, speed and fluidity of movement to deduce affective states (65).

Although valuable insights for affective states can be gained if face and body are approached separately (preferably facial expressions), the literature shows that combining information from different affective states will provide more reliable recognition (e.g. (66)).

4.4. Physiological reactions

Measuring internal physiological reactions connected to the affective state requires employment of specific sensors, such as electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG), and sensors measuring electrodermal activity (EDA). Since these sensors measure the internal body changes, such as heart bit rate, blood pressure, skin conductance, and respiration rate, they relate emotions to medical applications. Physiological signals are considered as a specific information channel for emotional reactions and can provide potentially more reliable data. The latter can be explained with the following: "true" emotions can be hidden in facial expressions or speech, at least to some extent. This is because people sometimes choose not to express their emotions to others, even though they react emotionally within themselves. While emotions can be overlooked sometimes in other communication channels, they can be identified by measuring physiological data.

In recent years measuring physiological signals as a means of identifying a user's emotional state has became popular due to the advanced development and availability of unobtrusive sensors that can provide constant monitoring of a user's internal emotional reaction (3). Physiological sensors have been integrated into clothing and jewellery; skin conductivity sensor in shoes, blood volume pressure sensor in earrings, respiration sensor in a sports bra; and numerous others (68). These sensors enabled user monitoring under various every-day conditions. Examples include monitoring drivers' physiologic reactions during real-world driving situations to measure driver's stress level in normal everyday surroundings (69), preventing sleep-deprived traffic accidents (70) or monitoring military aircraft pilots in close combat situations (71).

Existing methods are based on statistical analysis of recorded physiological signals from the autonomous and central nervous system (72). The majority of the experiments have intentional elicitation of certain emotions or emotional categories (e.g., anger, fear, sadness happiness, disgust, arousal, valence) rather than recordings of spontaneous emotions (73-74). The elicitation methods mostly use static images (73; 75; 76) video clips (74) or music sounds (77). Many research efforts have reported successful recognition results. Haag et al. (73) have managed to recognize the two main emotional dimensions, valence and arousal, with success rates of 90% and 97%, respectively. Nasoz et al. (74) reported a recognition rate of up to 84% for all six basic categories of emotion (happiness, sadness, anger, fear, disgust and surprise). Four emotions (joy, sadness, pleasure, sadness) were recognized with a high success rate of around 90% (78). Recognition of a subset of 3-4 emotions from the basic six in about 50 subjects has resulted in a 78% success rate (76). Haley and Picard conducted important studies for detecting stress in real world situations (75). They found that heart bit rate and skin conductivity are more informative physiological signals. They reported 97% recognition rate among different drivers over multiple days of monitoring. A high accuracy of stress detection has also been achieved using non-intrusive physiological sensors in the work of Barreto and Zhai (79).

The examples from the literature have all focused on specific sets of emotional categories and high success rates have been reached. It is noticeably, however, that higher recognition rates where achieved in studies that focused on measuring a smaller and more limited set of emotional information channels.

4.5. Synopsis

In this section we summarise and synthesize the research findings which may appear as an arbitrary itemizing of the AC research agenda. We examined representative conference proceedings themes of the AC research community, namely, the biennial series of the International Conference on Affective Computing and Intelligent Interaction (ACII), and comparing with the modality/communication channel oriented approach above (see first two columns in Table 1). The substance of AC research is encapsulated, as admitted by the editors of the ACII2007 volumes (80), within the investigation of theories and mechanisms through which machines capable of recognizing, modelling and expressing emotions and other affective phenomena may be created. The efforts are expected to contribute to the "creation of machines that allow for the establishment of sustainable and affective relations with humans..." (80). Affective relation and emotion may be a determinant of health and computers may indirectly influence health. Consequently, it is imperative that work in medical informatics becomes relevant to any such evolution. The latter is properly described in the next section.

Related Communication Channel (Output Modality) in this paper	**ACII 2007 Thematic areas**	**Related MIE 2006 Thematic Areas**
Visual	Affective Facial and Body Expression and Recognition	biomedical signal and image processing
Audio	Affective Speech Processing	biomedical signal processing
Text	Affective Text and Dialogue Processing	decision support, electronic health records (through natural language processing)
Internal Physiological	Recognising Affect Using Physiological Measures	biomedical signal processing
All	Computational Models of Emotion and Theoretical Foundations	knowledge representation & management, clinical bioinformatics
All	Affective Databases, Annotations, Tools and Languages	electronic health records, knowledge representation & management
Audio	Affective Sound and Music Processing	biomedical signal processing
All	Affective Interactions: Systems and Applications	ubiquitous health care systems
All	Affective Evaluations	health information systems and management

Table 1. A merging view of the communication channels discussed as expression/output modalities in this paper and the relevance of thematic areas in AC and MI through their appearance in representative conferences like ACII and MIE.

5. Applying Affective Computing in Medical Informatics

According to authoritative definitions, medical informatics can be considered as the "science of studying the theoretical and practical aspects of information processing and communication, based on knowledge and experience derived from processes in medicine and health care delivery" (81). The last decade has also witnessed an expansion of medical informatics. Specifically, bioinformatics has been included, stemming from the synergy between medical informatics and biological research largely through the notion of Virtual Physiological Human (82), thereby leading to a greater area of biomedical informatics (83).

Table 1 attempts to circumscribe possible research overlaps which lead to synergies between AC and medical informatics. Being affect-aware and able to express affect, computers and computer systems may be utilised in various medical and healthcare domains and for various purposes. In the next section we present some of the healthcare related application areas that have received much attention by the AC society.

Affective Computing and Medical Informatics (AmI) combines unobtrusive and possibly invisible computing, advanced networking technologies and interfaces aware of human presence and is, often connected to Pervasive or Ubiquitous Computing[1] (84). This set of technologies is thought to meet certain user needs and can engage in intelligent interaction (spoken, gesture based, etc.). AmI has been considered as one of the most important emerging technologies that will be interrelated with AC in the future (1). Alcaniz and Rey (85) referred to AC, together with intelligent user interfaces, as areas that can potentially shape the development of the ambient intelligence field. Additionally, Cearreta et al. (86) have included AC as a component of AmI and listed significant benefits in their attempt to establish synergies between the two areas. Zhou et al. (87) further extended the research in this direction by proposing a framework for emotion-aware AmI. Within this framework AmI technologies are applied to improve users' everyday activities through monitoring and recognizing their emotional state and, by acting emotionally, potentially to have a positive influence on a user's emotions. The interrelation between AC and AmI is now motivating research projects, one of which is the EU-FP6 funded CALLAS Integrated Project[2]. CALLLAS aims to develop a multimodal architecture, including emotional aspects, and to support applications in the new media business scenario with an "AmI" paradigm. Recently, affective technologies have been considered as key topics in conferences related to AmI, such as Artificial and AmI AISB'07[3], 7th International Conference and Workshop on AmI and Embedded Systems 2008[4], 14th Portuguese Conference on Artificial Intelligence EPIA'09[5]) or vice versa (e.g. AmI as a one of the key topics at the Affective Computing and Intelligent Interaction - ACII 2007 conference). AmI, together with AC, has been reported in the final report by the IST Advisory Group (ISTAG) regarding "Scenarios for AmI in 2010" (88). AmI is expected to have considerable implications for the future of health technologies, affecting the technology,

[1] One may note the relevance of this with the Personalised Healthcare vision of the MI research community

[2] http://www.callas-newmedia.eu

[3] http://www.aisb.org.uk/convention/aisb07/#callForPapers

[4] http://www.fh-kiel.de/index.php?id=5246

[5] http://epia2009.web.ua.pt/eac/

ergonomics, project management, human factors and organizational changes in the structure of the relevant health services (89).
AmI technologies are co-related and complement the tele-home health care area. Tele-home health care platforms enable patient monitoring without the need for physical presence by the caregiver, due to the availability of Internet-based communication technologies and unobtrusive wireless wearable sensors. Tele-home health care technologies facilitate collection of vital sign data remotely (ECG, blood pressure, oxygen saturation, heart and breath sounds), verification of compliance with medicine regimes, assessment of mental or emotional status and much more (90). Emotion-aware communication between the caretaker and care recipient in tele-home health care environments has shown to be of vital importance to the patient (91). Existing systems employ multi-modal interface including avatars (able to express emotions), to remind the patient of a medication, or to show empathy to the user when a certain negative emotion is detected. (6, 68).
The successful application of AmI and tele-home health care platforms is due to the advanced development and availability of unobtrusive sensors and software tools that recognize meaningful emotional patterns, thereby enabling continuous and objective monitoring of a user's internal emotional reaction (1; 3).
Earlier in the paper we discussed that stress is one of the most significant affective states that is a "measurably important health factor" (3). As stated in (3), stress is considered as the number one health concern in New England and that part of USA, above AIDS, cancer or hypertension. Monitoring and recognizing stress through available physiological sensors (e.g. ECG) can facilitate development of innovative HCI applications that could contribute to decreasing stress levels. Human behaviours seem to be qualitatively different when manipulating objects during a stressful event as compared to manipulating them during neutral events (92). Existing approaches attempted to recognize stress in various settings: hand movements in stressful situations (93), using mobile systems (93) or recognition of driver's stress (94). Stress is characterized by highly expressive reactions in multiple modalities, which can be measured using the existent AC recognition methods: facial expressions (95), physiological signals (94), body movements (93) or speech (96). The recognition success in the majority of the examples is higher than the average human detection.
Research projects in this area are slowly but steadily emerging, such as the Affective Health System (97) which aims to empower mobile users to find patterns of their own stress levels throughout their daily lives. It is likely that certain AC related (keynote) presentations are also appearing in International Medical Informatics conferences and workshops (see for example the AMIA 2008 symposium[6]).
There are many aspects of the research in the autism interventions domain that would require AC technologies. Computer systems represent a controlled environment with minimum or no distractions, which is crucial in the education process for autistic children (98). The evidence shows that autistic children enjoy using computers and have affinity towards computer applications (99). The Affective Computing Group (ACG) at MIT and the Autism Research Centre (ACR) at Cambridge[7] are among the pioneers in this field. Working closely with autistic persons lead to development of different methods, applications and technologies for emotion recognition and expression. Various Computer-Aided Learning systems have been developed for treatment of autistic mental disorder (100; 101;102). Emotionally expressive avatars have also been incorporated in collaborative virtual environments for autistic persons

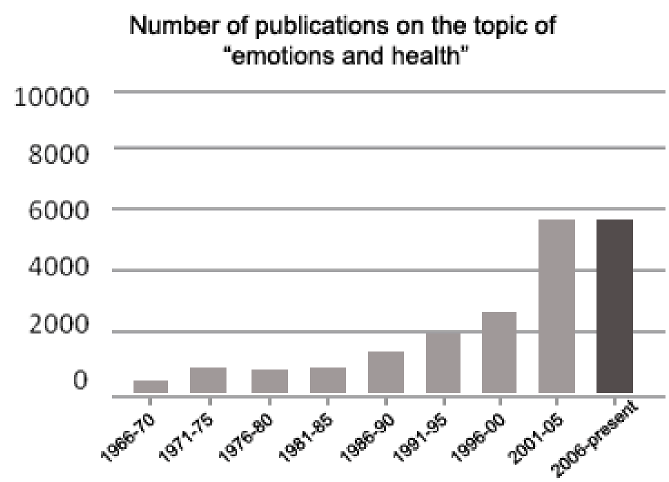
[6] http://symposium2008.amia.org/
[7] http://www.autismresearchcentre.com/arc/default.asp

(103). The Affective Computing Group developed innovative wearable sensors, including algorithms that recognise human affective states effectively and are which applicable for autistic individuals (104). Additionally, the Affective Social Quotent project has helped autistic children learn emotions using physical objects such as dolls (105).

The research into the use of AC technologies for improving the cognitive, social and communicative abilities of people with autism is making continuous progress and has been identified recently as one of the most attractive areas within AC. Autism was one of the key areas for future research at the high profile workshop/discussion meeting, held recently at the Royal Society in London, on "Computation of Emotions in Man and Machines"[8], where the pioneers in AC and related fields have discussed the challenges and benefits of AC applications for autism.

6. Discussion

Research has shown that the medical community has started to realising the crucial role emotions play in the preservation of human's mental and physical health. Research focusing on the relation between emotions and health (medicine) has rapidly increased in recent years. Since its emergence in the late 90's AC has provided the medical community with technologies that help with better understanding of emotions, identifying their impact on health, and offering new techniques for diagnosis, therapy, and treatment of emotionally-influenced diseases.
An illustrative representation of the number of published articles in PubMed Medline® using the terms "emotion" and "health" from 1966 to 2000 is shown in (2); figure 5 represents a modified and updated version of that representation up to 2009).



COMMENT: The bars in the graph need to touch each for a correct representation; please avoid color-coding

Figure 2. Publications on the topic of "emotions" and "health" in the MEDLINE database, based on [2] with the addition of contemporary amendments

[8] http://royalsociety.org/event.asp?id=7433

Figure 2 shows a continuous growth of publications within each 5-year period, with a substantial increase in the last decade. It is possible that the increased number of publications is due to an expansion of psychology research related to emotion and health, rather than a mere advancement of AC technologies and unobtrusive wearable sensors. But even that is itself a strong argument for an already observed and an anticipated future expansion of AC, since research in psychology may drive the emergence of such applications and lead to further examples of enabling technology solutions. A similar observation can be made with respect to the field of elderly care, where psychology research related to cognitive training of the elderly has recently lead to an expansion of Ambient Assisted (Elderly) Living research and technological applications (106; 107). It is believed that the increased rate of research studies that are related to "emotion and health" and combined with AC and advances in communication technologies, may potentially facilitate the development of innovative AC originated medical applications. Tele-home healthcare, AmI, ubiquitous monitoring and e-learning are just few of the areas where the potential of AC has already been realized and initial applications have emerged.

Additional projects on AC and health that were funded by the European Commission under the 6th and 7th Framework Programmes (FP6 & FP7)[9] are provided in Table 2 of the Appendix.

Utilization of AC in medical practice is only in its infant phase and many domains are yet to be explored. For instance, medical education, through the area of e-learning can benefit form AC. Affective speech synthesis and multi-modal emotion expression through virtual characters have started to become popular in virtual community applications for elderly people or even children with certain impairments.

The number and variety of AC applications in the medical domain depends on the development pace of AC technologies and the creation of synergies in the greater medical informatics/e-health research community. With the advancement in each of the sub-areas of AC (text, speech, face and gestures expression, physiology), we can expect substantial increases in the interest for emotionally-intelligent applications in the medical informatics domain.

The application of AC technologies parallels the advancement of the existing state of the art and the introduction of new and improved methods. We have seen that the existing emotion recognition or expression systems have many limitations, which is one of the main reasons for the slow expansion of the AC field. Namely, the majority of the recognition methods from all of the channels and modalities are focused on acted versus naturally induced emotions. The attention remains primarily on a small set of basic emotions and the affective channels (speech, face, body etc.) are still approached separately rather than multimodaly, which is how humans communicate emotions. The recognition sensors, specifically for monitoring physiological reactions, are still obtrusive and their application for various settings is quite complex.

AC and medical informatics are currently two separate disciplines with only limited synergies realized until recently. But classical psycho(physio)logical research is no longer enough for advancing either one in the fields of common interest. There is probably a need for a new integrative approach, where data and information driven common applications can benefit from sharing common analyses and interpretation (knowledge) methodologies, as well as system and protocol design and experimentation approaches. The similarity of this decade's witnessed synergy between bio-informatics and medical informatics along data and information at all

[9] http://cordis.europa.eu/home_en.html

levels (the notion of the VPH vision) is relevant here. For instance, the elucidation and promotion of the synergy between AC and medical informatics may follow the successful paradigm of the emergence of biomedical informatics. The actual VPH may be employed as a vehicle of this synergy, since its various modelling levels (from genes and cells to systems/human/society) relates strongly to the future of AC research[10] and the emergence of new medical informatics related application areas. For example, we foresee that data and information about (personal) emotional conditions may be directly relevant to advances in Electronic Health Records (EHRs) (111; 112) and their expansion to meet the recent biomedical informatics research challenges. The idea of personalised, patient-centered healthcare systems can not be separated easily from work in AC, as the data about ones mental/emotional/mood state are very relevant to a patient's well being or therapy effectiveness, and, thereby, relevant to the electronic health record content. It may, therefore, be here where classical and new developments are all integrated.

Furthermore, AC and medical informatics researchers have addressed different issues, and perhaps used different methodologies, with funding from distinct sources. This may now be changed, as exemplified by European Commission calls for application where a specific collaboration between two fields is slowly but surely outlined (see Table 3 in Appendix). Both AC and medical informatics research communities however, are active in machine learning, natural language processing, image and signal analysis, knowledge representation and data mining in large databases.. By increasingly sharing common goals and projects, as well as enabling technologies necessary for the development of solutions proposed in each other's areas, both communities may benefit. Some medical informatics professionals have claimed the need for more emphasis on addressing AC issues related to the study of medical scientific challenges (113). Interestingly enough, AC pioneers have also been orienting some of their research towards application of AC technologies in the medical domains, such as research into emotions and autism or creation of wearable devices that can measure emotions through physiological signals for heath purposes.

In conclusion, it appears that a number of gaps will be overcome through the synergy of AC and medical informatics. The synergetic research agenda may be initiated along important axes of ICT research, namely: (1) prevention of (emotionally related) diseases, for example, by addressing the effect of emotion on the prevalence of certain diseases and utilisation of ICT systems for measuring health parameters and motivating people to manage their health; (2) Personal Health Systems for promoting and expanding the notion of interoperable PHS, home health care (eHealth) systems along the landscape of electronic health records, continuous health care, and always across multilingual and multicultural environments; and (3) collaborative (enterprise and educational) learning environments, including educational interventions for therapeutic reasons (e.g. autism). The amount of work and projects reviewed herein witness an ambitious and optimistic synergetic future of the field of Affective Medicine.

[10] It was mentioned earlier that BMI (genes and biomarkers) research into "stress and anxiety" may well advance the scientific grounds and the impact of stress management AC systems and projects.

7. Appendix - EU call and projects related to AC and health

Project name	Description
COSPATIAL	The project aims at developing collaborative technologies designed to promote the learning of social competence by children who are typically developing and those with Autistic Spectrum Disorders (ASD).
TeaCheR - Training System for Disabled Children based on Affective Computing and Virtual Reality	TEACHER is a research and technological development project designed to prove the technical and practical viability of mixed Virtual Reality (mVR) and affective computing applied to support children in developing new learning skills and increasing the autonomy and the knowledge of those affected by weak short term memory disability by developing an open interoperable multimodal user platform able to provide advanced 3D audio-visual training content.
AUBADE	The AUBADE project provides an innovative tool that will lead professionals to a deep study, analysis, understanding, and comprehension of neurological diseases and human emotions.
INTREPID	The INTREPID project aims at developing a multi-sensor wearable system for the treatment of phobias and situational anxiety. The project actively contributes to the treatment of phobias in an unobtrusive, personalized and intelligent manner.

Table 2. EU projects related to AC and health

Programme	Specific Objectives Relevant to AC and MI	Year
FP7 Cooperation Work Programme: Health	HEALTH-2007-2.2.1-3: Neurobiology of anxiety disorders HEALTH-2007-2.2.1-8: From mood disorders to experimental models HEALTH-2007-2.2.1-10: Childhood and adolescent mental disorders	2007
FP7 Cooperation Work Programme: ICT Challenge 7	Challenge 7: ICT for Independent Living and Inclusion Objective ICT-2007.7.1: ICT and Ageing	2007
FP7 Cooperation Work Programme: ICT Challenge 5	Challenge 5: Towards sustainable and personalised healthcare Objective ICT-2009.5.1: Personal Health Systems Objective ICT-2009.5.3: Virtual Physiological Human	2008
FP7 Cooperation Work Programme: ICT Challenge 2	Challenge 2: Cognitive Systems, Interaction, Robotics Objective ICT-2009.2.1: Cognitive Systems and Robotics	2009
FP7 Cooperation Work Programme: ICT Challenge 4	Challenge 4: Digital Libraries and Content Objective ICT-2009.4.2: Technology-Enhanced Learning	2009
FP7 Cooperation Work Programme: FET PROACTIVE	Objective ICT-2009.8.5: FET proactive 5: Self-Awareness in Autonomic Systems but also: Computing and Communication Paradigms Living with ICT Widening the Horizon of ICT	2009

Table 3. Related EU calls where AC and its sub-areas appear already (and possibly be related to MI).

8. References

1. Picard RW. Affective Computing. 1st ed. The MIT Press; 1997.

2. Cacioppo J. Introduction: Emoton and Health. In: Handbook of Affective Stress. Oxford University Press; 2003.

3. Picard RW. Affective medicine: Technology with emotional intelligence. Future of Health Technology. 2001; 69-85.

4. Webster C. Medical affective computing: medical informatics meets affective computing Stud Health Technol Inform. 1998; 52.

5. Smith RN, Frawley WJ. Affective Computing: Medical Applications. In: Proceedings of HCI International (the 8th International Conference on Human-Computer Interaction): Ergonomics and User Interfaces. L. Erlbaum Associates Inc.; 1999. p. 843-847.

6. Prendinger H, Ishizuka M. What Affective Computing and Life-Like Character Technology Can Do for Tele-Home Health Care. In: Workshop on HCI and Homecare: Connecting Families and Clinicians (Online Proceedings) in conj. with CHI. 2004.

7. Bickmore TW, Picard RW. Establishing and maintaining long-term human-computer relationships. ACM Trans. Comput.-Hum. Interact. 2005; 12(2):293-327.

8. Glaser R, Pearl DK, Kiecolt-Glaser JK, Malarkey WB. Plasma cortisol levels and reactivation of latent Epstein-Barr virus in response to examination stress. Psychoneuroendocrinology. 1994 ;19(8):765–772.

9. Cohen S, Doyle WJ, Skoner DP, Rabin BS, Gwaltney JM. Social ties and susceptibility to the common cold. JAMA: The Journal of the American Medical Association. 1997 Jun; 277(24):1940–4.

10. Burg M. Stress, Behavior, and Heart Disease. In: Heart Book. Yale University School of Medicine, 2002.

11. Paulhaus D, Fridhandler B, Hayes S. Psychological Defense: Contemporary Theory and Research. In: Handbook of Personality Psychology. San Diego: Academic Press; 1997.

12. Vaillant GE. Ego mechanisms of defense and personality psychopathology. J Abnorm Psychol. 1994 ;103(1):44–50.

13. O'Leary A. Self-efficacy and health: Behavioural and stress-physiological mediation. Cognitive Therapy and Research. 1992 Apr; 16(2):229–245.

14. Scheier MF, Magovern G, Abbot RA, Matthews KA, Owens JF, Lefembre R, Carver CS. Dispositional optimism and recovery from coronary artery bypass surgery:

the beneficial effects on physical and psychological well-being. Journal of personality and social psychology. 1989; 57(6):1024–1040.

15. Wiebbe DJ, Williams PG. Hardiness and health: a social psychophysiological perspective on stress and adaptation. Journal of social and clinical psychology. 1992; 11(3):238–262.

16. Stone AA, Cox DS, Valdimarsdottir H, Jandorf L, Neale JM. Evidence that secretory IgA antibody is associated with daily mood. J Pers Soc Psychol. 1987; 52(5):988–93.

17. Middleton R, Byrd E. Psychosocial Factors and Hospital Readmission Status of Older Persons with Cardiovascular Disease. Journal of Applied Rehabilitation Counseling. 1996; 273–10.

18. Martin LR, Friedman HS, Tucker JS, Tomlinson-Keasey C, Criqui MH, Schwartz JE. A life course perspective on childhood cheerfulness and its relation to mortality risk. Personality and Social Psychology Bulletin. 2002; 28(9):1155.

19. Kimonides VG, Spillantini MG, Sofroniew MV, Fawcett JW, Herbert J. Dehydroepiandrosterone antagonizes the neurotoxic effects of corticosterone and translocation of stress-activated protein kinase 3 in hippocampal primary cultures. Neuroscience. 1999 Mar; 89 (2):429-36.

20. Eysenck MW. Anxiety and cognition: A unified theory. Hove, UK: Psychology Press; 1997.

21. Fox E, Russo R, Bowles RJ and Dutton K. Do threatening stimuli draw or hold visual attention in sub-clinical anxiety? Journal of Experimental Psychology: General, 2001; 130(4), 681-700.

22. Pennebaker JW, Mehl MR, Niederhoffer KG. Psychological aspects of natural language use: Our words, our selves. Annual review of psychology. 2003; 54(1):547–577.

23. Liu H, Lieberman H, Selker T. A model of textual affect sensing using real-world knowledge. In: Proceedings of the 8th international conference on Intelligent user interfaces. Miami, Florida, USA: ACM; 2003. p. 125–132.

24. Fellbaum C. WordNet An electronic lexical database. Cambridge, MA.: MIT Press; 1998.

25. Valitutti A, Strapparava C, Stock O. Developing affective lexical resources. PsychNology Journal. 2004 ;2(1):61–83.

26. Kim S, Hovy E. Identifying and analyzing judgment opinions. In: Proceedings of the main conference on Human Language Technology Conference of the North American Chapter of the Association of Computational Linguistics; 2006. New York, New York: Association for Computational Linguistics; 2006. p. 200–207.

27. Whissell C. The dictionary of affect in language. The Measurement of Emotions: Theory, Research and Experience. 1989; 113.

28. Subasic P, Huettner A. Affect analysis of text using fuzzy semantic typing. IEEE Transactions on Fuzzy Systems. 2001; 9(4):483–496.

29. Nasukawa T, Yi J. Sentiment analysis: capturing favorability using natural language processing. In: Proceedings of the 2nd International Conference on Knowledge Capture; 2003; Sanibel Island, FL, USA; 2003. p. 70–77.

30. Dellaert F. Recognizing emotion in speech. In: Proceedings of the ICSLP '96. 1996.

31. Petrushin VA. Emotion in speech: Recognition and application to call centers In Engr. 1999; 7-10.

32. Yu F, Chang E, Xu Y, Shum H. Emotion Detection from Speech to Enrich Multimedia Content. In: Advances in Multimedia Information Processing – PCM'01; 2001. p. 550–557.

33. Yacoub S, Simske S, Lin X, Burns J. Recognition of emotions in interactive voice response systems. In: Proc. Eurospeech; 2003; Geneva. p. 1-4.

34. Neiberg D, Elenius K, and Laskowski K. Emotion recognition in spontaneous speech using GMMs. In: Proc. of Interspeech 2006; Pittsburgh.

35. Roy D, Pentland A. Automatic spoken affect classification and analysis. In: Proceedings of the 2nd International Conference on Automatic Face and Gesture Recognition (FG '96). IEEE Computer Society; 1996. p. 363.

36. Montero JM, Gutierrez-Arriola JM, Palazuelos S, Enriquez E, Aguilera S, Pardo JM. Emotional speech synthesis: from speech database to TTS. In: Fifth International Conference on Spoken Language Processing. ISCA; 1998.

37. Zovato E, Pacchiotti A, Quazza S, Sandri S. Towards emotional speech synthesis: a rule based approach. In: Fifth ISCA Workshop on Speech Synthesis. ISCA; 2004.

38. Burkhardt F, Sendlmeier WF. Verification of acoustical correlates of emotional speech using formant-synthesis. In: ISCA Tutorial and Research Workshop (ITRW) on Speech and Emotion. ISCA; 2000.

39. Edgington M. Investigating the limitations of concatenative synthesis. In: Fifth European Conference on Speech Communication and Technology; 1997.

40. Heuft B, Portele T, Rauth M. Emotions in time domain synthesis. In Proceedings of the Fourth International Conference on Spoken Language – ICSLP'96;1996. p. 1974-1977 vol.3.

41. Reilly J, Klima ES, Bellugi U. Once more with feeling: affect and language in atypical populations. Development and Psychopathology. 2008; 2(04):367-391.

42. Gillberg C. Asperger syndrome and high-functioning autism (Review). British Journal of Psychiatry. 1998; 172200–209.

43. Dara C, Monetta L, Pell MD. Vocal emotion processing in parkinson's disease: reduced sensitivity to negative emotions. Brain Research; 2008 Jan 10; 1188:100-11.

44. Ekman P. Emotion in the human face. Cambridge University Press; 1982.

45. Ekman P, Friesen WV. Facial Action Coding System. Consulting Psychologist Press; 1977.

46. Lisetti CL, Schiano DJ. Automatic facial expression interpretation: where human-computer interaction, artificial intelligence and cognitive science intersect. Perspective. 2000; 8(1):185-235.

47. Cohn JF, Kanade T. Use of automated facial image analysis for measurement of emotion expression. Handbook of Emotion Elicitation and Assessment; 2007.

48. Kanade T, Cohn JF, Tian YL. Comprehensive database for facial expression analysis. In Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition (FG'00), Grenoble, France; 2000. p. 46-53.

49. Schmidt K, Cohn JF, Tian YL. Signal characteristics of spontaneous facial expressions: Automatic movement in solitary and social smiles. Biological Psychology; 2003; 65: 49-66.

50. Cohn JF, Schmidt KL. The timing of facial motion in posed and spontaneous smiles. International Journal of Wavelets, Multiresolution and Information Processing; 2004; 2: 1-12.

51. Cootes, TF, Edwards GJ, Taylor CJ. Active appearance models. IEEE Transactions on Pattern Analysis and Machine Intelligence; 2001. p. 681-685.

52. Wen Z, Huang TS. Capturing subtle facial motions in 3D face tracking. International Conference on Computer Vision, Nice, France; 2003. p. 1343-1350.

53. Valstar MF, Pantic M, Patras I. Motion history for facial action detection in video. In Proceedings of the IEEE Conference on Systems, Man, and Cybernetics, the Hague, the Netherlands; 2004. p. 635-640.

54. Cassell J, Sullivan J, Prevost S and Churchill EF. Embodied conversational agents. Cambridge, MA.: MIT Press; 2000.

55. Bailenson J, Beall A, Blascovich J, Raimundo M, Weishbush M. Intelligent agents who wear your face: user's reactions to the virtual self. Transfer Report. Center

for the Virtual Environment and Behaviors Department of Psychology, University of California, Santa Barbara; 2000.

56. George P, McIllhagga M. The communication of meaningful emotional information for children interacting with virtual actors. In: Affective interactions: towards a new generation of computer interfaces. Springer-Verlag; 2000. p. 35–48.

57. Hone K. Empathic agents to reduce user frustration: The effects of varying agent characteristics. Interact. Comput. 2006; 18(2):227-245.

58. Moore D, Cheng Y, McGrath P, Powell NJ. Collaborative virtual environment technology for people with autism. Focus on Autism and Other Developmental Disabilities. 2005; 20(4):231.

59. Luneski A, Konstantinidis E, Hitoglou-Antoniadou M, Bamidis PD. Affective computer-aided learning platform for autistic children. In: Proceedings of the 1st Workshop on Child, Computer and Interaction, Crete, Greece: 2008.

60. Woodworth M, Waschbusch D. Emotional processing in children with conduct problems and callous/unemotional traits. Child Care Health Dev. 2008; 34(2):234-244.

61. Shiffrar M, Pinto J. Visual analysis of bodily motion. In: Common mechanisms in perception and action: Attention and Performance. Oxford: Oxford University Press; 2002.

62. Burgoon JK, Jensen ML, Meservy TO, Kruse J, Nunamaker JF. Augmenting human identification of emotional states in video. In: Proceedings of the Intrnational Conference on Intelligent Data Analysis. 2005.

63. Bianchi-Berthouze N, Kleinsmith A. A categorical approach to affective gesture recognition. Connection Science. 2003; 15(4):259-269.

64. Kapur A, Kapur A, Virji-Babul N, Tzanekatis G, Driessen PF. Gesture-based affective computing on motion capture data. In: Affective computing and intelligent interaction - ACII 2005. Springer Verlag; 2005.

65. Bernhardt D, Robinson P. Detecting Affect from Non-stylised Body Motions. In: Proceedings of the 2nd international conference on Affective Computing and Intelligent Interaction. Lisbon, Portugal: Springer-Verlag; 2007. p. 59–70.

66. Castellano G, Kessous L, Caridakis G. Emotion Recognition through Multiple Modalities: Face, Body Gesture, Speech. In: Affect and Emotion in Human-Computer Interaction. 2008. p. 92–103.

67. Balomenos T, Raouzaiou A, Ioannou S, Drosopoulos A, Karpouzis K, Kollias S. Emotion analysis in man-machine interaction systems. Machine Learning for Multimodal Interaction. 2004; 318-328.

68. Norman DA. The Invisible Computer. Cambridge, MA.: MIT Press; 1999.

69. Healey JA, Picard RW. Detecting stress during real-world driving tasks using physiological sensors. IEEE Transactions on Intelligent Transportation Systems. 2005; 6(2):156-166.

70. Papadelis C, Chen Z, Kourtidou-Papadeli C, Bamidis PD, Chouvarda I, Bekiaris E, Maglaveras N. Monitoring sleepiness with on-board electrophysiological recordings for preventing sleep-deprived traffic accidents. Clin Neurophysiol. 2007 Sep; 118(9):1906-1922.

71. Skinner MJ, Simpson PA. Workload issues in military tactical airlift. The International Journal of Aviation Psychology. 2002 ;12(1):79-93.

72. Andreassi JL. Psychophysiology: Human Behavior and Physiological Response. 5th ed. Lawrence Erlbaum Associates; 2000.

73. Haag A, Goronzy S, Schaich P, Williams J. Emotion recognition using bio-sensors: First steps towards an automatic system. Lecture Notes in Computer Science. 2004; 306: 836-48.

74. Nasoz F, Alvarez K, Lisetti L, Finkelstein N. Emotion recognition from physiological signals using wireless sensors for presence technologies. Cogn. Technol. Work. 2004; 6(1):4-14.

75. Picard RW, Vyzas E, Healey J. Toward machine emotional intelligence: analysis of affective physiological state. IEEE transactions on pattern analysis and machine intelligence. 2001; 23(10):1175-1191.

76. Bamidis PD, Frantzidis C, Konstantinidis E, Luneski A. An Integrated Approach to Emotion Recognition for Advanced Emotional Intelligence. San Diego: 2009.

77. Wagner J, Kim J, Andre E. From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification. In: IEEE International Conference on Multimedia and Expo, 2005. ICME 2005. 2005. p. 940-943.

78. Lisetti C, Nasoz F, LeRouge C, Ozyer O, Alvarez K. Developing multimodal intelligent affective interfaces for tele-home health care. Int. J. Hum.-Comput. Stud. 2003; 59(1-2):245-255.

79. Barreto A, Zhai J, Adjouadi M. Non-intrusive physiological monitoring for automated stress detection in human-computer interaction. In: Human–Computer Interaction. 2007. p. 29-38.

80. Paiva A, Picard R, Aylett R, Kolias S, Ortony A, Tao J, Prada R. Preface, In: Paiva A, Prada R, Picard R, editors. In: Proceedings of the 2nd International Conference on Affective Computing and Intelligent Interaction (ACII 2007); 2007. Berlin: Springer-Verlag; 2007.

81. Van Bemmel J, Musen MA, editors. Handbook of medical informatics. Houten: Springer-Verlag; 1997.

82. e-Health trends. http://ec.europa.eu/information_society/ehealth, last access May 10, 2009.

83. Maojo V, Kulikowski CA. Bioinformatics and medical informatics: collaborations on the road to genomic medicine? JAMIA. 2003; 10(6):515-522.

84. Riva G. AmI in health care. CyberPsychology & Behavior. 2003; 6(3):295-300.

85. Alcaniz, M, Rey B. New technologies for AmI. In: AmI: The Evolution of Technology, Communication and Cognition towards the Future of HCI. 2005. p. 3-16.

86. Cearreta I, Lopez J, Hernandez C, Garay N, Grana M, Alvarez A. Affective computing as a component of AmI. In: Proceedings of the 10th Joint Conference on Information Sciences 2007; 2007; Salt Lake City, Utah, USA. p. 1580-1586.

87. Zhou J, Yu C, Riekki J, Karkkainen E. AmE framework: a model for emotion-aware AmI. In: Proceedings of the 2nd International Conference on Affective Computing and Intelligent Interaction (ACII 2007); 2007. Berlin: Springer-Verlag; 2007.

88. Ducatel K, Bogdanowicz M, Scapolo F, Leijten J, Burgelman J. ISTAG Scenarios For AmI in 2010; 2001. http://cordis.europa.eu/ist/istag-reports.htm

89. Riva G, Vatalaro F, Davide F, Alaniz M. AmI: The Evolution of Technology, Communication and Cognition towards the Future of HCI. IOS Press, Fairfax; 2005.

90. Crist TM, Kaufman SB, Crampton KR. Home telemedicine: a home health care agency strategy for maximizing resources. Home Health Care Management Practice. 1996 Jun 1; 8(4):1-9.

91. Kenner AN. The effect of task differences, attention and personality on the frequency of body-focused hand movements. Journal of Nonverbal Behavior. 1984 Mar; 8(3):159–171.

92. Alonso MB, Varkevisser M, Hekkert P, Keyson D. Exploring manipulative hand movements during a stressful condition. In: Proceedings of the 2nd Affectove Computing and Intelligent Interaction conference (ACII 2007); 2007. p. 757–758.

93. Liu KKL. A personal, mobile system for understanding stress and interruptions. MIT, Cambridge; 2004.

94. Healey J, Picard R. Smartcar: detecting driver stress. In: Proceedings of the 15th International Conference on Pattern Recognition; 2000.

95. Metaxas D, Venkataraman S, Vogler C. Image-based stress recognition using a model-based dynamic face tracking system. In: Computational Science - ICCS 2004; 2004. p. 813–821.

96. Worgan S, Moore RK. Enabling reinforcement learning for open dialogue systems through speech stress detection. In: The Fourth International Workshop on Human-Computer Conversation; 2008; Bellagio, Italy.

97. Hook C. A holistic approach to ubiquitous stress management. In: Proceedings of UbiComp 2009, In Press.

98. Fabri M, Moore D. The use of emotionally expressive avatars in collaborative virtual environments. In: Proceeding of Symposium on Empathic Interaction with Synthetic Characters, at Artificial Intelligence and Social Behaviour Convention 2005. 2005.

99. Murray D. Autism and information technology: therapy with computers. Autism and learning: a guide to good practice. 1997; 100–117.

100. Enyon A. Computer interaction: an update on the avatar program. Communication, Summer. 1997; 18.

101. Eddon G. Danny's rooms. In: Proceedings of the John Hopkins National Search for Computing Applications to Assist Persons with Disabilities. IEEE Computing Society press; 1992.

102. Green SJ. Computer-Based Simulations in the Education and Assessment of Autistic Children. In: Rethinking the Roles of Technology in Education. Massachusetts Institute of Technology, Cambridge, MA.: 1993. p. 334–336.

103. Luneski A, Konstantinidis E, Hitoglou-Antoniadou M, Bamidis PD. Affective Computer-Aided Learning Platform for Autistic Children. Chania, Crete, Greece: 2008.

104. Kaliouby R, Picard R, Barron-Cohen S. Affective computing and autism. Annals of the New York Academy of Sciences. 2006; 1093 (1 Progress in Convergence: Technologies for Human Wellbeing):228–248.

105. Blocher K, Picard RW. Affective social quest: emotion recognition therapy for autistic children. Socially Intelligent Agents: Creating Relationships with Computers and Robots. 133–140.

106. Frantzidis C, Bamidis PD. Description and future trends of ICT solutions offered towards independent living: the case of the LLM project. In: Proceedings of the 2nd ACM International Conference on PErvasive Technologies Related to Assistive Environments (PETRA 2009); Greece Jun; 2009, In Press.

107. Brain Fitness. http://www.brainfitness.com. last access May 12, 2009.

108. Knaup P, Bott O, Kohl C, Lovis C, Garde S. Electronic patient records: moving from islands and bridges towards electronic health records for continuity of care. Meth Inform Med. 2007; 46:31-46.

109. Meystre S. Electronic patient records: some answers to the data representation and reuse challenges findings from the section on patient records. In: Geissbuhler A, Haux R, Kulikowski C, editors. IMIA Yearbook of Medical Informatics 2007. Methods Inf Med 2007; 46(1): 47-49.

110. Bamidis PD, Papadelis C, Kourtidou-Papadeli C, Pappas C, Vivas A. Affective computing in the era of contemporary neurophysiology and health informatics. Interacting with Computers. 2004; 16(4):715-721.