HUMAN TECHNOLOGY

An Interdisciplinary Journal on Humans in ICT Environments ISSN: 1795-6889

www.humantechnology.jyu.fi Volume 11 (1), May 2015, 71–93

ON THE CONVERGENCE OF AFFECTIVE AND PERSUASIVE TECHNOLOGIES IN COMPUTER-MEDIATED HEALTH-CARE SYSTEMS

Rebeca I. García-Betances
Life Supporting Technologies (LifeSTech)
Superior Technical School of
Telecommunications Engineers
Polytechnic University of Madrid
Spain

Giuseppe Fico
Life Supporting Technologies (LifeSTech)
Superior Technical School of
Telecommunications Engineers
Polytechnic University of Madrid
Spain

Dario Salvi
Life Supporting Technologies (LifeSTech)
Superior Technical School of
Telecommunications Engineers
Polytechnic University of Madrid
Spain

Manuel Ottaviano
Life Supporting Technologies (LifeSTech)
Superior Technical School of
Telecommunications Engineers
Polytechnic University of Madrid
Spain

María T. Arredondo
Life Supporting Technologies (LifeSTech)
Superior Technical School of
Telecommunications Engineers
Polytechnic University of Madrid
Spain

Abstract: *This paper offers a portrayal of how affective computing and persuasive technologies can converge into an effective tool for interfacing biomedical engineering with behavioral sciences and medicine. We describe the characteristics, features, applications, present state of the art, perspectives, and trends of both streams of research. In particular, these streams are analyzed in light of the potential contribution of their convergence for improving computer-mediated health-care systems, by facilitating the modification of patients' attitudes and behaviors, such as engagement and compliance. We propose a framework for future research in this emerging area, highlighting how key constructs and intervening variables should be considered. Some specific implications and challenges posed by the convergence of these two technologies in health care, such as paradigm change, multimodality, patients' attitude improvement, and cost reduction, are also briefly addressed and discussed.*

Keywords: *affective computing, persuasive technology, computer-mediated health care, patient engagement, patient motivation.*

DOI: http://dx.doi.org/10.17011/ht/urn.201505061741

INTRODUCTION

Technology challenges in the 21st century are far greater than those ever encountered before by humankind. Several initiatives have been launched aiming to better define and understand the impending research ideas that need to be debated. A panel of prominent engineers and scientists was convened in 2008 by the US National Academy of Engineering to identify such challenges. As a result, 14 major Grand Engineering Challenges for the 21st century were selected (National Academy of Engineering of the National Academies, 2008). Also, a new initiative was launched at the international level by the national academies of engineering of the United Kingdom, the United States of America, and China: the Global Grand Challenges Summit in London in March 2013 (Royal Academy of Engineering, 2013). That summit's objective was to identify the most pressing common global challenges facing the world, in an attempt to guide the development of the necessary collaboration, networks, and tools that would allow tackling these problems. In a similar line of thinking, there have been specific initiatives to define future challenges in addressing problems in the life sciences by using engineering methodologies. One such initiative was the recent 2013 IEEE Life Sciences Grand Challenges Conference in Washington, DC (IEEE Lifesciences, 2013).

Addressing biomedical and health issues through cognitive science and information technology methodologies for enriching life experience represents one of the challenges faced by life sciences engineering. In such a context, novel approaches in personalized human–computer health systems (Kaptein, Markopoulos, de Ruyter, & Aarts, 2015) would motivate patients towards complementary self-management of their own diseases. Presumed benefits of applying self-care methods include lower costs for the health-care system, increased patient satisfaction, patient engagement, and improved perception of the patient's own health condition.

The convergence of different technologies and disciplines into a unified whole is an essential requirement to open up new opportunities. Information sharing and networking are also crucial elements for pursuing these goals. Investments in health-care convergence innovation would lead to better engaged and more informed patients, a better understanding of diseases, and new systems and structures to control and treat diseases (Sharp, 2012).

The convergence of affective computing (AC) and persuasive technologies (PTs) represents a particularly attractive proposition. Both technologies emerged at about the same time as the concept of artificial intelligence and, together with sensing and computing techniques, have reached developmental maturity levels in recent decades, allowing the behavioral sciences to be connected with the engineering world. At the same time, an ever-increasing knowledge base and recent advances experienced by health technologies are giving rise to new challenges. Many important present health issues may be adequately addressed by combining these two disciplines, in concert with networking integration and information sharing.

This paper offers a comprehensive, descriptive overview of present opportunities for the profitable integration of AC and PTs research areas into health-care systems. It is particularly intended for a general audience as an introductory overview of the state of the art of these two technologies from the point of view of their possible convergence into computer-mediated assistive technologies for the health-care sector.

Personal persuasion is a different strategy from mass media persuasion in that personal persuasion can easily make use of feedback and coherence. Computer-mediated persuasion can provide a more emotionally effective and complementary means than face-to-face interaction in the adoption of a behavioral shift (Di Blasio & Milani, 2008). Patient engagement and behavior can be significantly improved by the use of PTs. Recent studies have shown the beneficial effect of incorporating affective and emotional aspects within the design of PTs (Nguyen & Masthoff, 2009; Reitberger et al., 2009; Torning & Oinas-Kukkonen, 2009). Such fusion may be accomplished in a natural way by including emotional information within the interaction process between the computer, as the PTs agent, and the patient, as the user. Because human–computer interaction (HCI) is influenced by users' personal differences, affect and motivation can be fundamental to shaping individual performance (Chalmers, 2003). Affective and emotional aspects can be integrated into PTs through the well-known techniques of AC (Picard, 1995, 1999, 2000, 2002). AC has the potential to significantly enhance PTs by way of improving user experience (H. Li & Chatterjee, 2010). The close relationship between emotions and health, the availability of technologies that facilitate the application of AC in numerous areas, and the ubiquity of computers constitute strong motivations to pursue the development of AC/PTs applications (Luneski, Konstantinidis, & Bamidis, 2010).

This paper is structured in the following way: We begin by providing a brief overview of advances in PTs, a description of AC as it pertains to PTs, and a discussion on PTs and AC specifically aimed at the field of health care. Then, we suggest potential challenges and describe anticipated future trends within the health domain. Finally, we outline the basis for designing future research frameworks. Definitions, techniques, and typical application examples are included throughout.

CHARACTERISTICS OF PERSUASIVE TECHNOLOGY

The concept of PTs, also known as persuasive computing, was described by Fogg (2003, p. 1) as "computer-based tools designed for the purpose of changing people's attitudes and behaviors." It was introduced on the basis of technology's potential for enabling the interactive functioning of persuasive techniques utilizing user's inputs, needs, and context. Fogg also proposed that the change of people's attitudes and behavior as a result of persuasion implies a voluntary desire to change (Ijsselsteijn, de Kort, Midden, Eggen, & van den Hoven, 2006). In this light, PTs can be looked upon as a subdivision of HCI, a discipline that has emerged in the last decade by combining multiple other fields to create a new science of motivation and desire. The design of persuasive systems using communication stimuli to influence and change people's behavior and/or attitude involves several scientific domains and fields, such as behavioral sciences, neuroscience, genetics, social networking, game design, computing, biomedical engineering, and so forth (Institute for the Future [IFTF], 2010; H. Li & Chatterjee, 2010; Mintz & Aagaard, 2012).

In the book *Persuasive Technology*, Fogg (2003) divided persuasion into three scopes or views: as a tool, as media, and as a social role. We offer a summary of Chatterjee and Price's (2009) strategies used by each of these scopes.

Persuasion as a Tool

In this view, persuasive systems are used to facilitate a change of attitudes and/or behaviors by making desired outcomes easier to achieve. Various strategies can be applied for this purpose using several types of PT tools. Such strategies may be separated into the following categories (Fogg, 2003):

- Simplification. This involves influencing users to assume a particular behavior by proposing simple tasks through computing technologies.
- Guidance. This strategy, sometimes known as tunneling technology (Kraft, Schjelderup-Lund, & Brendryen, 2007), guides users through a predetermined sequence of actions or events with the purpose of increasing their engagement and behavioral effectiveness.
- Customization. Persuasive effectiveness for inducing changes in users' attitudes or/and behaviors may be increased by tailoring the information provided to them to their relevant individual needs, interests, personality, and so forth. The strategy is also known as tailoring technology (Kreuter, Farrell, Olevitch, & Brennan, 2000).
- Just-in-time intervention. The strategy consists of suggesting to the user the adoption of a certain behavior at the most opportune moment (Madsen, el Kaliouby, Goodwin, & Picard, 2008). Intervening at the right time represents a fundamental aspect for enhancing the effectiveness of a PT.
- Self-monitoring. This helps users achieve goals in the course of modifying their attitudes and/or behaviors (Maas, Hietbrink, Rincka, & Keijsers, 2013; Ouweneel, Le Blanc, & Schaufeli, 2013). Self-monitoring works in real time by providing feedback to users as they track their status through various measurements of their physical state, location, progress, and so forth.
- Surveillance. Persuasion is attained through the user's observation of others. The strategy enhances the prospect of modifying the user's own behavior in a specific way by monitoring and learning from the behavior of others.
- Conditioning. This is achieved through positive reinforcement as an effective rewarding tool to motivate the change or reshaping of current habits or complex behaviors.

Persuasion as Media

In this view, convincing simulated experiences are presented to the users in an attempt to persuade them to change or shape their attitudes or/and behaviors. Several types of simulations used in PTs can have a direct and significant impact on modifying users' attitudes and behaviors in the real world.

- Simulated cause-and-effect scenarios. Simulations of the relationship between a cause and its effect in a particular situation are presented to users. These simulations enable users to explore and experiment with various attitudes and behaviors, experiencing the consequences of their actions within a safe environment. The new attitudes and behaviors are then applied by the users in real-world situations.
- Environment simulations. Users are exposed to simulated environmental situations aimed at persuading by motivation and reward to adopt and practice a given target behavior (Nakajima & Lehdonvirta, 2011). Such simulated environments help users to control their exposure to new or frightening situations and facilitate adopting another person's perspective.

- Object simulations. Providing concrete experience simulations in everyday contexts, the simulations motivate attitude changes in daily routines. This approach refers to the use of portable simulations of everyday life to emphasize the impact of certain behaviors.

Persuasion as a Social Role

In this view, social interaction is used by the persuasive systems to allow users to feel motivated by their desire to behave appropriately according to the community's prevailing desirable behavior. Such motivation leads to a predisposition of the user's attitude. Computers can provide motivational and persuasive elements as user feedback. A social agent can be persuasive by rewarding users with positive feedback, such as praise. Modeling a target behavior or attitude can be attained by providing motivational support through social comparison and awareness of others' emotions (Eligio, Ainsworth, & Crook, 2012; Leonard & Haines, 2007; Mumm & Mutlu, 2011).

Most of the technologies to motivate people's behavior that have been reported to date deal mainly with personal lifestyle-related health management. There exist numerous actual cases that illustrate the usefulness of PTs for encouraging people to adopt healthy lifestyle habits (Merino Albaina, Visser, van der Mast, & Vastenburg, 2009). User-centered strategies that are based on ambient information systems have been proposed as an effective means for this purpose (Pousman & Stasko, 2006). For example, the use of aesthetically pleasing applications to provide easily comprehensible representations of supportive information is a proven valuable tool for motivating elders to exercise (Rodríguez, Roa, Morán, & Nava-Muñoz, 2012).

In addition to lifestyle-related health issues, the use of persuasive systems in the field of mental illness is another important target for computer-mediated intervention. One such example is the MONARCA system[1], a mobile Android-based application and Web-based system intended for self-assessment, activity monitoring, historical overview of data, coaching, self-treatment, and data sharing in mental illness intervention (Brinkman, 2013; Marcu, Bardram, & Gabrielli, 2011). Other typical applications and implementations of PTs for health management include cloud-based systems (Yang, Chiang, Liu, Wen, & Chuang, 2010); persuasive wearable technology systems (Ananthanarayan & Siek, 2012); persuasive obesity intervention using Web-based mobile technology (Ping, Poh, Meng, Husain, & Adnan, 2012); systems that allow interactive, structured, multimodal delivery of clinical advice (Iyengar, Florez-Arango, & García, 2009); and several types of systems that aim to manage chronic diseases, support self-care, and encourage adherence to treatment therapies.

Many challenges still remain for using PTs in improving computer-mediated health-care systems (Munson, 2012). Whatever the persuasion strategy to be pursued, it is of paramount importance to thoroughly assess its effectiveness. Evaluation targets should include, among other technical aspects, behavioral indicators such as users' attitude change toward the issue, trustworthiness of the system, perceived information quality, and the intention to conform to the requested behavior (Wilson & Lu, 2008).

MAJOR FEATURES OF AFFECTIVE COMPUTING

Affect represents a major personality construct that has been considered one of the three classical divisions of psychology (Forgas, 2001). It can refer to feeling, emotion, mood, attitude, preferences, or personality. A number of scales have been proposed to measure affective state. A commonly used measure of positive and negative affect is the I-PANAS-SF schedule, an international short-form 10-item scale version of the original 20-item Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988). I-PANAS-SF presents internal reliability, cross-sample and temporal stability, cross-cultural factorial invariance, and convergent and criterion-related validities (Thompson, 2007).

The concept of AC was introduced in 1995 by Professor Rosalind W. Picard (1995), founder and director of the Affective Computing Research Group at the Massachusetts Institute of Technology (MIT; n.d.) Media Lab. Since then, this concept has been systematically described and explained by Picard in several monographs (1995, 1999, 2000, 2002). The MIT Media Lab (n.d., para. 1) defines AC as "computing that relates to, arises from, or deliberately influences emotion or other affective phenomena."

This subject combines engineering and computer science with other disciplines, such as psychology, sociology, education, cognitive science, and neuroscience. The overall objective in AC is to devise computer systems that can identify the affective states of user and, accordingly, to adapt and respond to user changes in real time. To that end, AC also aims to reduce the communicative disparity between humans' emotions and computers (Iovane, Salermo, Giordano, Ingenito, & Mangione, 2012; Wu, 2012). AC broadens HCI by incorporating emotional communication and the appropriate means for handling and managing affective information (Picard, 1999). Hudlicka (2013) provided a thorough review of and introduction to the emerging research area of affective HCI and the requirements for effective and desirable HCI. Earlier, Picard (2003) described the research challenges in the area of AC, especially in regard to the affect aspect of HCI. Some of the generally desirable or expected abilities of affective technology would include user affect detection and interpretation, system affective state synthesis and expression, and the ability to influence user affect (Broekens & Brinkman, 2013).

Affective Computing Phases

Most AC systems nowadays follow a closed-loop scheme consisting of three phases: affect recognition, affect modeling, and affect control (Wu, 2012). Affect recognition involves recognizing the subject's affects from a subject's body signals. Affect modeling entails the use of models to appropriately describe the relationship between the subject's environment and the subject's affect. Affect control consists of altering the environment to shift the subject's affect towards a desired state. Emotion-aware computing applies affective techniques in modeling emotion (van den Broek, 2013). Computational models of affective adaptation and emotion dynamics have been proposed (Steephen, 2013). Once the relationship between the user's affect and the environment is modeled, the user's pertinent emotions can be identified by some of the commonly used detection methods (see below); an affect control stage outputs a signal to change the environment and move the user's emotions towards a desired state.

Applications

According to Picard (1999, 2000), three basic types of system applications using AC exist (see also Calvo & D'Mello, 2010): systems that only detect the emotions, systems that express what a human would perceive as an emotion, and systems that "feel"[2] an emotion. A wide variety of applications that are based on AC have been and are still being developed in diverse domains, such as medicine, telehomecare, cognitive training, learning, and gaming (Frazier, Huang, Kraus, Chang, & Maheswaran, 2013; M. Kim, Kim, Lee, & Choi, 2013; Pastor-Sanz, Vera-Munoz, Fico, & Arredondo, 2008; Postolache et al., 2012; Zhang & Wang, 2013).

Detection Methods and Techniques

The measurement of human affect plays a crucial role in AC. However, affect detection is very complex because emotions are conceptual qualities that cannot be directly measured. Human affect states must be expressed and communicated through various inference channels, such as text, audio (voice), facial expressions, and body gestures, as well as explicit physiological changes, such as blood pressure, heart rate, breathing, and sweating. Six basic, universally recognized emotions were defined in 1972 by Ekman, Friesen, and Ellsworth: anger, disgust, fear, joy, sadness, and surprise. This list has been expanded by other researchers (e.g., Calvo & D'Mello, 2010; Ekman & Davison, 1994; Iovane et al., 2012). Methods and techniques for detecting affectivity have been proposed on the basis of these definitions (Luneski et al., 2010). The most prominent techniques are based on one or more of the following measurement modalities.

- Facial expressions. Detection techniques are based on the assumption that there exist distinctive human facial expressions associated with each of the basic emotions. Numerous techniques abound for the detection and recognition of facial features and expressions, and although no standard measurements for such are available, some facial expression databases have been compiled (Pantic, Valstar, Rademaker, & Maat, 2005; Shih & Chuang, 2008; Wang et al., 2013).
- Body language and posture. Posture-based affect detection has been widely used, although too few studies have been carried out to date to allow a definitive analysis. Recognizing all the movements present in a spontaneous situation is a difficult task, and attempting to classify them into emotional categories is even harder. However, the use of body postures as a way for detecting emotional states offers clear advantages over other nonverbal measures, such as facial expression detection and paralinguistic features of speech. Many studies have been carried out to describe how specific body features may be used to recognize specific affective states (Kleinsmith & Bianchi-Berthouze, 2013; Tan, Schöning, Luyten, & Coninx, 2013). Some researchers have focused on assessing only a reduced set of basic emotions, in a manner similar to that used in the facial expression technique, in order to simplify the posture-based affect detection process (Calvo & D'Mello, 2010; Iovane et al., 2012; Luneski et al., 2010). Head movement as a postural response also has been used to estimate attentional mechanisms when monitoring users' cognitive engagement (Dirican & Göktürk, 2012).
- Emotional vocal expressions. This detection technique relies on recognizing emotions through the affective information transmitted in speech or other utterances that include

any type of vocalization. Recognition of emotion in speech is one of the key disciplines in speech analysis for next generation human–machine interaction (Matsumoto & Ren, 2011; Yeh, Pao, Lin, Tsai, & Chen, 2011; Dai, Han, Dai, & Xu, in press). The transmission of affect is communicated through the message itself (what is said) and through the nonverbal paralinguistic features of expression (how it is said, rate of speech, voice tone, etc.). The detection and decoding of paralinguistic features has not been clearly established yet, but it is known that the use of prosody and nonlinguistic vocalizations (cries, laughs, etc.) facilitates the detection of basic emotions. Both of them have been used to decode affective signs beyond basic emotions, such complex emotions as stress, depression, boredom, and excitement (Calvo & D'Mello, 2010).

- Physiological indicators. Emotions can be recognized also by measuring physiological data or signals that constitute a direct information channel for emotional reactions (Bamidis, Papadelis, Kourtidou-Papadeli, Pappas, & Vivas, 2004). Some AC systems already use physiological signals to identify different emotions and to detect patterns that correspond to the expression of a particular emotion. Methods that use physiological data or signal recognition usually are included within what is referred to as machine learning techniques (Calvo & D'Mello, 2010; Luneski, Bamidis, & Hitoglou-Antoniadou, 2008; Luneski et al., 2010). Several noninvasive measurements can be acquired by recording electrical signals produced by the brain, heart, muscles, and skin (Iovane et al., 2012). These measurements can be obtained nowadays through unobtrusive wearable sensing devices or through devices embedded in the surrounding environment. The foremost signals conveniently used for affection recognition include electromyogram (EMG), electrodermal activity (EDA), electrocardiogram (ECG, or EKG), electrooculogram (EOG), and electroencephalography (EEG), as well as some other more recent techniques in the field of neuroimaging (Calvo & D'Mello, 2010; Hamdi, Richard, Suteau, & Allain, 2012; Luneski et al., 2008; Rutkowski et al., 2011).
- Text features. Detecting emotions through text implies assessing the hidden data that might be present in written language or in oral communication transcriptions. Osgood and his colleagues (Osgood & Treng, 1990; Osgood, May, & Miron, 1975) studied how people express emotions through text in trying to understand how text triggers different emotions. Three dimensions were defined to represent words on the basis of word-similarity ratings provided by participants from various cultures (Calvo & D'Mello, 2010). These three dimensions are evaluation (how a word refers to an event that is pleasant or unpleasant), potency (how a word is associated to an intensity level), and activity (whether a word has an active or passive connotation).
- Multimodality. As already mentioned, affect recognition can involve the integration of different modalities, such as facial expression, body language and posture, vocal emotion recognition, and text analysis, as well as a variety of physiological signals (Gunes, Piccardi, & Pantic, 2008; Poria, Cambria, Hussain, & Huang, 2015). Audio and visual-based emotion analysis and processing were the subject matter of a new challenge that was convened in 2013 with the goal of providing a common benchmark test set for individual multimodal information processing, as well as to compare the relative merits of these two approaches to emotion recognition and to determine to what degree the fusion of these two approaches is achievable and helpful (Audio/Visual Emotion Challenge [AVEC], 2013; Valstar et al., 2013).

In some cases, the information obtained by any one technique on its own is ambiguous, unreliable, or does not exactly match the user's real emotions. In addition, some emotions can be manifested simultaneously via multiple modes. For example, anger can be expressed by facial, vocal, body posture, and physiological changes. Based on these premises, some studies have proposed a technique called multimodality, which integrates information obtained from several sources and methods (Calvo & D'Mello, 2010; Iovane et al., 2012). In a recent study, Iovane et al. (2012) proposed the use of data fusion, feature fusion, and decision fusion (see Table 1) to combine or "fuse" signals from several sensors. The type of fusion to use depends on the kind of information measured by the sensors.

A process of merging EMG signals from the face, ECG data, respiration rate, and skin conductivity has been used to identify emotional states of individuals with Huntington's disease and Parkinson's disease (Pastor-Sanz et al., 2008). The physical, psychological, and cognitive abilities of automobile drivers with diabetes have been used to detect and prevent hypoglycemic events by combining data from patients' biosignals and environment sensors (J. Kim, Ragnoni, & Biancat, 2010). This multimodality strategy was recently applied in a European research project in which the mood status of patients with bipolar disorder was predicted by combining data acquired from several Heart Rate Variability (HRV), ECG, respiration, and subject voice sensors; from sleep quality and speech rate algorithms; and from subjective symptoms reports using the Bauer internal state scale (Personalized Monitoring Systems for Care in Mental Health Project [PSYCHE], n.d.).

Table 1. Characteristics of the Multimodality Fusion Types (Iovane et al., 2012).

Type	Characteristics
Data fusion	Performed on each signal's raw data Applied only when the signals have the same temporal resolution Not commonly used because of its sensitivity to noise
Feature fusion	Performed on the set of features extracted from each signal (e.g., statistical measurements and other unique features from each sensor) Used in multimodal user interfaces and in AC
Decision fusion	Performed by merging the output of the classifier for each signal Most commonly used approach for multimodal HCI

AFFECTIVE COMPUTING/PERSUASIVE TECHNOLOGIES CONVERGENCE IN THE HEALTH-CARE DOMAIN

The purpose of this paper is not to propose new AC/PTs convergence strategies. Rather, we intend to provide a comprehensive overview of significant state of the art approaches. Emotions have a significant impact on overall human health because both medical and physical health care are clearly influenced by such factors as self-esteem and self-efficacy. Negative emotions can have a detrimental impact on health, and it is known that positive emotions significantly enhance people's overall well-being (Luneski et al., 2010). This premise has led to the search for improvements and new developments within the domain of affective technologies. The term *affective medicine* was introduced by Picard in 2002 to signify the use of emotionally aware and emotionally responsive computers in medicine (Luneski et al., 2010;

Picard, 2002). Past developments regarding emotions in the field of medicine have focused primarily on two scenarios: virtual environments for health care and the use of emotional support computers for psychotherapy. Extrinsic and intrinsic drivers play important roles as behavioral determinants of users' motivation to engage in virtual environments (Verhagen, Feldberg,van den Hooff, Meents, & Merikivi, 2012).

On the other hand, persuasion influences affective and cognitive responses and behavior intention (C. Y. Li, 2013). PTs and AC have been used in a variety of domains. One important such domain is health-care management through patients' self-managing their chronic diseases. The various persuasive strategies proposed within these domains involve increasing patients' motivation or changing their behavior through the use of technology. Embedded sensors and real-time, context-aware technologies are beginning to provide advancements for essential just-in-time feedback that can be used to present a health-related message at an appropriate time to encourage people to make healthier decisions (IFTF, 2010; Intille, 2004). Most of the research on PTs to date has utilized mobile smart phones as a primary platform. Other nontraditional devices, such as digital frames, mirrors, and desks, also have been used as persuasive instruments (Mukhtar, Ali, Belaid, & Lee, 2012). Table 2 presents examples of typical applications of PTs applied in the health domain, with explanation of the programs provided in the Endnotes.

The convergent use of AC and PTs as information and communications technologies in the field of health care highly increases the potential for the development of innovative clinical applications. Some typical examples of such potential are the solutions created by some EU-funded projects, such as those of PSYCHE (Valenza, Gentili, Lanatà, & Scilingo, 2013), MOTIVA (Domingo et al., 2011), METABO (Fico et al., 2011), and HeartCycle (Ottaviano et al., 2011; Reiter, Tesanovic, Martinez-Romero, 2013). The convergence of AC and PTs can open up additional possibilities for developing and implementing persuasive strategies. We now highlight the AC/PTs convergence strategies currently integrated into the most relevant and useful health-care-related applications.

Treatment Adaptation

Patients' compliance to strict medical treatment frequently can fail if the protocol conflicts with the routine of their daily activities, which are themselves highly dependent on the time of the day, the day of the week, and the season of the year. Adapting treatments to a patient's life is therefore of paramount importance. An AC/PTs-convergent system could dynamically detect

Table 2. Some Typical Current Applications of Persuasive Technologies in the Health Domain.

Areas	Application Examples[3]
Social Networking	The "Patients Like Me" Web site (PLM)
Health-care Systems	Philips Motiva TeleHealth Platform (MOTIVA) HeartCycle Project (HCP) Controlling Chronic Diseases Related to Metabolic Disorders project (METABO)
Well-being	Sports applications: Nike+, Polar WearLink+ (NPA; PWL) Diet and nutrition applications (DNT)
Preventive Medicine	Symptom tracker (PST)
Psychotherapy	Virtual Reality Therapy (VRT) for fears, phobias, and disorders

these situations and adapt treatments within some safety ranges defined by caregivers (e.g., It is Christmas: Eat what you want, but things will be stricter afterwards).

Patients' Motivation

Raising motivation levels involves measuring and reacting to the patient's mood. Measuring motivation requires the use of both direct and indirect means of detection (e.g., asking if the patient took the pill vs. checking if the pill was taken). An AC/PTs-convergent system would react to the patient's current motivational state by using an appropriate persuasive strategy to modify the patient's emotional status.

Noninvasive Intuitive User Interaction

Because people generally do not wish to be disturbed by machines, the system should minimize this disturbance. Reduced interference by the AC/PTs-convergent system may be achieved by ubiquitous-but-minimally-invasive monitoring, as well as by the use of various channels of communication (e.g., telephone, television), including indirect means, depending on the context. The current smart phone era opens up very interesting opportunities to offer simple and easy-to-use tools to promote healthy lifestyles (Cain & Martínez, 2012). Smart phones can be a starting point to collect informal medical data to be used to assess the user's well-being and that then becomes part of a personalized health record. These mobile devices also are used nowadays in medical practice for cardiovascular rehabilitation. At the same time, health records are presently shifting from a central model approach, in which only professionals in the health-care ecosystem generate and upload clinical information, to a shared model approach, in which patients as well are able to add their personal health information through smart personal devices.

The usefulness of mobile technology integration has been amply demonstrated (Quinn et al., 2011). Convergence of mobile technology, clinical and behavioral sciences, and clinical results, known as mobile-integrated therapy, embodies far-reaching platforms for patient–health-care provider interaction through bidirectional data collection and transfer. The adoption of a convergent AC/PTs could produce very effective tools for improving scalable and cost-effective health care for chronic diseases. Incorporating a mobile-integrated therapy into the electronic health record system of a multiphysician practice has already been used successfully for Type 2 diabetes treatment (Peeples, Iyer, & Cohen, 2013).

Implantable Micro and Nanotechnology

Recent innovations have brought about new generations of biomedical devices that epitomize the synergistic collaboration of medical, biomedical, and electrical scientists and engineers. Devices such as intraperitoneal glucose monitors and cardiovascular implantable electronics are typical examples of recent medical devices that directly and reliably measure biosignals in real time, as opposed to other technologies that detect indirectly (e.g., subcutaneous or capillary glycemic level). An AC/PTs-convergent health-care system could incorporate such innovative technologies for detection and monitoring.

Multimodality

Measured biosignals may be combined through multimodality with other signals or indicators to determine the effect of emotional status on health and vice versa. This synergy could be expanded to the behavioral sciences by the convergence of AC and PTs. The multimodality approach could dramatically improve the robustness of emotion recognition by correlating internally measured biosignals with other externally and indirectly measured signals. Such convergence would lead to an understanding of the effect of emotions on health and disease far more effectively than has been possible through the use of subjective-based associative studies, such as those that attempt to measure and associate stress through linking indicators extracted from questionnaires.

Through multimodality, straightforward biomarkers (such as Body Mass Index [BMI]) may be grouped with more sophisticated biosignals (obtained from implantable devices) to codify, map, and cluster information into patterns to represent potential risk indicators of psycho-clinical conditions.

Exploiting the Social Environment

We recommend that, in consultation with and with the consent of the patient, an AC/PTs-convergent health-care system should consider including the patient's existing social environment players: relatives, close family, friends, and colleagues. The already widespread use of social networks can be of great assistance for this purpose. The convergence of persuasive and affective paradigms could be a very useful tool for enhancing performance within this strategy.

PRESENT CHALLENGES FOR CONVERGENT AFFECTIVE COMPUTING/ PERSUASIVE TECHNOLOGIES IN HEALTH-CARE APPLICATIONS

The convergence of AC and PTs for health-care applications requires developing strategies based on new paradigms. How should these new paradigms be adopted? Specifically, what aspects are more relevant, and what technical challenges do we face? We offer below a few insights into some of the main challenges that need to be dealt with.

Changing Paradigms

Overall well-being, preventive monitoring, patient engagement, and treatment compliance are key features of the new health-care paradigm. Some people will accept PTs and AC readily, whereas others will reject such technologies as being too intrusive. The challenge for the future of AC/PTs convergence in health care will be to find an optimal balance between the prevalence of these technologies and people's willingness to be helped by them.

Multimodality

One of the most important technical challenges is the use of multimodal systems (Lisetti, Nasoz, Lerouge, Ozyer, & Alvarez, 2003); this aspect is viewed as a clear advantage over the mostly unimodal approaches being used today. In spite of the fact that multimodal technology is widely advocated by researchers (Jaimes & Sebe, 2007; Pantic, Sebe, Cohn, & Huang, 2005), it rarely is implemented by developers. Nevertheless, if significant contributions could be made in multimodality, it undoubtedly would have a positive impact on AC/PTs convergence in the fields of health care. Multimodality, therefore, is the logical next step in the development of future convergent AC/PTs systems.

Improving Patients' Compliance to Treatment

Patients' noncompliance to prescribed treatments is known to pose a serious health-care problem: About 50% of chronic patients in developed countries do not comply with treatments (de León Linck, Machado Bielemann, de Sousa, & Lange, 2007). Lifestyle choices also pose major problems (Chatterjee & Price, 2009). One's lifestyle, together with one's genetics, form the primary risk factors in a wide variety of illnesses (Manton, 1989). Therefore, it seems highly desirable to develop AC/PTs-convergent technologies that will help in persuading patients to improve their compliance to prescribed medical treatment as part of enhancing the quality of their life and their lifestyle behaviors.

Reducing Health-Care System Costs

Ubiquitous computing and, particularly, the pervasive availability of smart mobile phones and tablets—together with the progress of context-aware algorithms—offer new opportunities for developing useful applications in several areas of health care. The application market should promote AC/PTs-convergent designs to produce sustainable low-cost solutions that would attract and motivate consumers/patients to this new well-being concept. At the same time, the current swift progress in biosignal sensing, implantable devices, and nanotechnology should begin to offer additional capabilities to AC and PTs at reasonably affordable prices.

A final general inference that can be drawn is that the major overall challenge facing the successful implementation of AC/PTs health applications rests upon the ability to devise paths for the widespread and inexpensive incorporation of these technologies into future health-care processes. New concepts in AC/PTs convergence worth researching require advancing computer-mediated patient motivation to adopt and retain healthier behaviors. Increasing the awareness and acceptance of these technologies by health-care administrators and professionals—and the willingness of patients and formal and informal support caretakers to adopt them—are two of the still unresolved tasks that undoubtedly would facilitate future progress in this field.

PROVISIONS FOR AFFECTIVE COMPUTING/PERSUASIVETECHNOLOGIES CONVERGENCE RESEARCH FRAMEWORKS

Convergent AC/PTs has great potential for developing useful applications for behavioral intervention. Researchers around the world are presently working on possible applications in the educational, medical, and marketing fields. Such systems must be able to measure both short-term emotions and longer term moods (Geller, 2014). Monitoring emotion-triggered bodily sensations is an essential tool for emotion recognition in the convergent AC/PTs realm. Different emotional states can be associated with topographically distinct and statistically separable but culturally universal bodily sensation maps. These maps have been constructed recently using the computer-based, topographical self-report method emBODY (Nummenmaa, Glerean, Hari, & Hietanen, 2013). Once emotional signals are generated in an affective dimensional space from detected emotions, they must be mapped to useful outputs. Mapping can be accomplished, even in the presence of noise, using probabilistic and decision-theoretic reasoning combined with predictive models from affect control theory, a comprehensive social psychological theory of human social interaction (Hoey, Schröder, & Alhothali, 2013).

Because the effectiveness of assistive technologies in health care and well-being is greatly enhanced by motivation, affective–motivational factors represent important issues to consider when developing assistive technologies for supporting healthy living (Ferring, Reljic, & Roelofsma, 2012). Substance abuse treatment (Chen et al., 2012; Marsch et al., 2014) and affective learning programs (Wang, Ko, Huang, Liu, & Li, 2014; Ruggiero, 2015) are some representative examples. Affective technology can play an important role in enhancing system connectedness (Patel et al., 2014). Online Internet-delivered intervention for weight-related healthy lifestyle behavior modification is common nowadays, and its availability is continuously increasing. A systematic review regarding its reach, long term effectiveness, and use has been recently published (see Kohl, Crutzen, & de Vries, 2013).

It is expected that PTs systems that incorporate AC would be more effective for computer-mediated persuasion in patient engagement than those that do not. Appropriate research frameworks for such AC/PTs convergence should serve as a plan to outline possible fertile directions of future research in this emerging field.

Designing research frameworks to guide and further pursue this fusion must focus on defining key study directions that highlight pertinent key groups of constructs and intervening variables. Studying and advancing AC/PTs convergence in health-care applications should proceed, for the most part, along the following general directions: conceptualization of constructs and variables pertaining to the convergence of persuasive and affective paradigms in health care, operationalization of the conceptual structure, development of execution strategies for health-care applications, system implementation, and performance assessment.

Developing appropriate conceptual definitions of key constructs is essential. Expressions of functionally related experiences, attitudes, and behaviors can be used as indicators to be grouped into hypothetical constructs. Such constructs entail more than merely the procedures used to measure them. They should be able to predict a range of behaviors in the phase of operationalization of this convergence, thus allowing the observable to be related to the theoretical framework. Properly specifying measurement models that relate the constructs to their indicators is also essential (MacKenzie, Podsakoff, & Podsakoff, 2011).

The intervening variables that influence the modification of patient attitudes and behaviors and their potential relationships with affective state must be identified and verified. Because of the existence and intensity of mood, neither affect nor emotion can be directly measured; indirect measures must be used, such as facial expression, choice of vocabulary, loudness, tone of voice, and biosignals. Likewise, the contribution of AC-mediated interventions to the effectiveness of PTs must be thoroughly assessed. In this context, validating the measures of constructs represents a critical aspect that should be given special attention, to assure that measurement tools truly represent the constructs to be inferred from them (Shadish, Cook, & Campbell, 2002).

Because persuasion is an intentional action-guiding attempt to change attitudes or behaviors, careful attention should be given to the ethical implications of an AC/PTs-convergent system design. Examples of general ethical principles relevant to persuasive design can be found in the literature (Berdichevsky & Neuenschwander, 1999; Karppinen & Oinas-Kukkonen, 2013; Nickel & Spahn, 2012; Pedersen, Khaled, & Yannakakis, 2012).

Future research frameworks for the convergence of AC and PTs in computer-mediated health-care systems should identify and scrutinize patient and care provider behaviors that could effectively promote, remind, support, guide, and assist with recovery or the improvement of specific clinical health parameters. The theoretical aspects of both technologies should be given particular attention. There are many challenges and needed improvements in the field of computational modeling of affective processes (Broekens, Bosse, & Marsella, 2013). Some proposed actions essentially refer to the systematic deconstruction and classification of psychological emotion theory's basic assumptions, so that emotions could be modeled using modularized general cognitive architectures, together with emotion theory unification and standardization by translation into common conceptual systems or common formal languages (Reisenzein et al., 2013). Other aspects of system design, such as structural configuration, process organization, workflow optimization, device connectivity, data exchange, software persistence, and system security, are, among others, key issues that must be addressed (Gil, Virgili-Gomá, García, & Mason, in press).

Treatment adaptation and personalization are also valuable system features worth considering. To that end, the most important aspects to be taken into consideration are the patients' social environments, their real-time motivation and emotional status modifications, intuitive user interaction and minimally invasive monitoring, and emotion recognition that combines measured biosignals with other external and undirected measured signals.

To fully realize the potential of introducing convergent AC/PTs solutions into computer-mediated health care for achieving a significant social and economic impact, it would be particularly valuable to gather ample and solid information to conduct comparative studies about the effectiveness of different emerging information and communications technologies and convergent AC/PTs as applied to specific health-care systems. The fusion of context-aware monitoring with the ability to provide timely personalized feedback, as embodied in the proposed convergence of AC and PTs, can bring about the development of powerful tools for daily behavior modification and wellness preservation. In this regard, the convergence of AC and PTs represents an excellent prospect to positively impact further progress of computer-mediated personal health applications.

ENDNOTES

1. MONARCA is the acronym for MONitoring, treAtment and pRediCtion of bipolAr Disorder Episodes. The MONARCA self-assessment system is a persuasive personal monitoring system to support the management of Bipolar Disorder patients, financed by Seventh Framework Programme of the EU. http://www.monarca-project.eu/
2. Systems that "feel" are systems that recognize the affective state of a person by sensors, ubiquitous solutions, or other technologies.
3. Some typical current applications of PTs in the health domain:

a) HeartCycle Project (HCP) is a part of the European Community's Seventh Framework Programme Project, grant no. FP7-216695. http://www.heartcycle.eu/

b) METABO, for controlling chronic diseases related to metabolic disorders, was part of the Information Society Technologies Programme of the European Commission’s Seventh Framework Programme, No. ICT-26270. http://cordis.europa.eu/project/rcn/85444_en.html

c) MOTIVA, Philips’ Motiva TeleHealth Platform is a content-rich and interactive TeleHealth system intended to allow chronically ill patients to effectively participate in the management of their disease. It incorporates a high level of flexibility, allowing its adaptation to the particular health condition and illness stage of individual patients. http://www.healthcare.philips.com/main/products/telehealth/products/motiva.wpd

d) Nike+ Applications (NPA) is a family of sports devices and applications funded and developed by a well-known shoe company. It uses dedicated connected devices, such as iPod Sensor, iPod Watch Remote, SportBand, FuelBand, SportWatch GPS, Polar Wearlink+ Transmitter; as well as a myriad of apps, such as Fuel App, Running App, Training Club App, iPod, Move, Kinect Training, Training, Basketball, etc. http://nikeplus.nike.com/plus/

e) Patients Like Me (PLM) is a social network that provides an effective way for patients to connect with other patients like them sharing their real-world health experiences to learn from and to help each other. By keeping records of their health over time, participants also contribute to research at organizations specialized on their health conditions, thereby helping advance medicine for all. http://www.patientslikeme.com/about

f) Pain and Symptoms Tracking (PST) applications are designed to work on portable personal platforms (smart-phones and tablets) to daily track of one or more chronic pain conditions and keep appropriate records for later analysis and sharing. A representative example is “My Pain Diary” a chronic pain and symptom tracker compatible with iPhone, iPad, and Android; Version 3.5.5 Mar 21, 2015: http://www.chronicpainapp.com/

g) Polar WearLink+ (PWL) technology uses a textile chest strap to pick up a person’s cardiac signals and wirelessly transfers that data via Bluetooth to a compatible application running in a mobile platform. More information may be found in the User Manual at: http://www.polar.fi/e_manuals/WearLinkPlus_Bluetooth/Polar_WearLink_Plus_Bluetooth_accessory_manual_English.pdf

h) There exists a growing number of diet and nutrition applications (DNA) intended to run on modern personal smart-phones and tablets. For some recent representative diet and nutrition trackers see, for example, 10 Best Diet & Nutrition Apps, by John Corpuz, Jan 13, 2015: http://www.tomsguide.com/us/best-diet-nutrition-apps,review-2308.html

i) Virtual Reality Therapy (VRT) for fears, phobias, and disorders is from Virtual Reality Medical Center. http://www.vrphobia.com/therapy.htm

REFERENCES

Ananthanarayan, S., & Siek, K. A. (2012, May). *Persuasive wearable technology design for health and wellness*. Paper presented at the Sixth International Conference on Pervasive Computing Technology for Healthcare (PervasiveHealth), San Diego, CA, USA.

Audio/Visual Emotion Challenge [AVEC]. (2013). *AVEC 2013: Challenge results*. Retrieved September 7, 2013, from the Third International Audio/Visual Emotion Challenge and Workshop Web site http://sspnet.eu/avec2013/

Bamidis, P. D., Papadelis, C., Kourtidou-Papadeli, C., Pappas, C., & Vivas, A. B. (2004). Affective computing in the era of contemporary neurophysiology and health informatics. *Interacting with Computers*, *16*(4), 715–721. doi: 10.1016/j.intcom.2004.06.009

Berdichevsky, D., & Neuenschwander, E. (1999). Toward an ethics of persuasive technology. *Communications of the ACM*, *42*(5), 51–58.

Brinkman, W. P. (2013). Current and future research directions in mental health computing. In *Proceedings of the International Conference on Computation and Communication Advancement* (pp. xvii–xxi), Kolkata, West Bengal, India: McGraw-Hill.

Broekens, J., Bosse, T., & Marsella, S. C. (2013). Challenges in computational modeling of affective processes. *IEEE Transactions on Affective Computing*, *4*(3), 242–245. doi: 10.1109/T-AFFC.2013.14

Broekens, J., & Brinkman, W. P. (2013). Affect button: A method for reliable and valid affective self-report. *International Journal of Human–Computer Studies*, *71*, 641–667. doi: 10.1016/j.ijhcs.2013.02.003

Cain. M., & Martínez, M. (2012). *Transforming bodies and lifestyles: Insights into inspiring behavior change.* Palo Alto, CA, USA: Institute for the Future. Retrieved on April 14, 2015, from http://www.iftf.org/uploads/media/IFTF_SR-1547_TransformingBodiesandLifestyles.pdf

Calvo, R. A., & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. doi: 10.1109/T-AFFC.2010.1

Chalmers, P. A. (2003). The role of cognitive theory in human–computer interface. *Computers in Human Behavior*, *19*, 593–607. doi: 10.1016/S0747-5632(02)00086-9

Chatterjee, S., & Price, A. (2009). Healthy living with persuasive technologies: Framework, issues, and challenges. *Journal of the American Medical Informatics Association*, *16*(2), 171–178. doi: 10.1197/jamia.M2859

Chen, Y. F., Madan, J., Welton, N., Yahaya, I., Aveyard, P., Bauld, L., Wang, D., Fry-Smith, A., & Munafò, M. R. (2012). Effectiveness and cost-effectiveness of computer and other electronic aids for smoking cessation: a systematic review and network meta-analysis. *Health Technology Assessment*, *16*(38), I–IV. doi: 10.3310/hta16380

Dai, W., Han, D., Dai, Y., & Xu, D. (in press). Emotion recognition and affective computing on vocal social media. *Information & Management.* doi: 10.1016/j.im.2015.02.003

de León Linck, C., Machado Bielemann, V. L., de Sousa, A. S., & Lange, C. (2007). The chronic patient in face of falling ill and treatment compliance. *Acta Paul Enferm*, *21*(2), 317–322.

Di Blasio, P., & Milani, L. (2008). Computer-mediated communication and persuasion: Peripheral vs. central route to opinion shift. *Computers in Human Behavior*, *24*, 798–815. doi: 10.1016/j.chb.2007.02.011

Dirican, A. C., & Göktürk, M. (2012). Involuntary postural responses of users as input to attentive computing systems: An investigation on head movements. *Computers in Human Behavior*, *28*, 1634–1647. doi: 10.1016/j.chb.2012.04.002

Domingo, M., Lupónad, J., González, B., Crespo, E., López, R., Ramos, A., Urrutia, A., Pera, G., Verdúde, J. M., & Bayes-Genis, A. (2011). Noninvasive remote telemonitoring for ambulatory patients with heart failure: Effect on number of hospitalizations, days in hospital, and quality of life—CARME (Catalan Remote Management Evaluation) study. *Revista Española de Cardiología*., *64*(4), 277–285. doi: 10.1016/j.rec.2010.10.032

Ekman, P., & Davison, R. J. (Eds.). (1994). *The nature of emotion: Fundamental questions*. New York, NY, USA: Oxford University Press.

Ekman, P., Friesen, W., & Ellsworth, P. (1972). *Emotion in the human face: Guidelines for research and an integration of findings*. Oxford, England: Pergamon Press.

Eligio, U. X., Ainsworth, S. E., & Crook, C. K. (2012). Emotion understanding and performance during computer-supported collaboration. *Computers in Human Behavior*, *28*, 2046–2054. doi: 10.1016/j.chb.2012.06.001

Ferring, D., Reljic G., & Roelofsma, P. (2012). "Why do we need it?"—An analysis of affective-motivational factors in the use of assistive technologies. In A. van Berlo, H. van den Heuvel, H. Herman Nap, I. Bierhoff, & W. Rijnen (Eds.), *Proceedings of the Fourth Ambient Assisted Living Forum* (pp. 577–582), Eindhoven, the Netherlands.

Fico, G., Fioravanti, A., Arredondo, M. T., Leuteritz, J. P., Guillén, A., & Fernandez, D. (2011, August–September). *A user-centered design approach for patient interfaces to a diabetes IT platform*. Paper presented at the 33rd Annual International Conference of the IEEE EMBS, Boston, MA, USA. doi: 10.1109/IEMBS.2011.6090274

Fogg, B. J. (2003). *Persuasive technology: Using computers to change what we think and do*. San Francisco, CA, USA: Morgan Kaufmann Publishers.

Forgas, J. P. (Ed.). (2001). *Handbook of affect and social cognition.* Mahwah, NJ, USA: Lawrence Erlbaum Associates, Inc., Publishers. ISBN 0-8058-3217-3

Frazier, S., Huang, C., Kraus, S., Chang, Y.-H., & Maheswaran, R. (2013). *Adaptive agent for player-specific fitness and health incentives in mobile location based games*. Paper presented at the Association for the Advancement of Artificial Intelligence Spring Symposium (2013AAAI; pp. 57–58), Palo Alto, CA, USA.

Geller, T. (2014). How do you feel? Your computer knows. *Communications of the ACM*, *57*(1), 24–26. doi: 10.1145/2555809

Gil, R., Virgili-Gomá, J., García, R., & Mason, C. (in press). Emotions ontology for collaborative modelling and learning of emotional responses. *Computers in Human Behavior*. doi: 10.1016/j.chb.2014.11.100

Gunes, H., Piccardi, M., & Pantic, M. (2008). From the lab to the real world: Affect recognition using multiple cues and modalities. In J. Or (Ed.), *Affective computing: Focus on emotion expression, synthesis and recognition* (pp. 185–218). Vienna, Austria: I-Tech Education and Publishing. Retrieved August 22, 2013, from http://doc.utwente.nl/65266/1/pantic_from_the_lab_book_chapter.pdf

Hamdi, H., Richard, P., Suteau, A., & Allain, P. (2012, June). Emotion assessment for affective computing based on physiological responses. Paper presented at the *IEEE World Congress on Computational Intelligence* (WCCI2012; pp. 1–8), Brisbane, Australia. doi: 10.1109/FUZZIEEE.2012.6250778

Hoey, J., Schröder T., & Alhothali, A. (2013). *Affect control processes: Probabilistic and decision theoretic affective control in human–computer interaction*, University of Waterloo School of Computer Science, Technical Report No. CS-2013-03. Retrieved August 22, 2013, from https://cs.uwaterloo.ca/sites/ca.computer-science/files/uploads/files/CS-2013-03_0.pdf

Hudlicka, E. (2013). To feel or not to feel: The role of affect in human–computer interaction. *International Journal of Human–Computer Studies*, *59*, 1–32. doi: 10.1016/S1071-5819(03)00047-8

IEEE Lifesciences. (2013). Web site for the 2013 IEEE Life Sciences Grand Challenges Conference. Retrieved January 10, 2015, from http://lsgcc.ieee.org/

Ijsselsteijn, W., de Kort, Y., Midden, C., Eggen, B., & van den Hoven, E. (2006). Persuasive technology for human well-being: Setting the scene. *Persuasive Technology*, *3962*, 1–5. doi: 10.1007/11755494_1

Institute for the Future (IFTF). (2010). *The future of persuasion: Why "persuasion" can't be a dirty word (Part 1)*. Retrieved September 15, 2013, from http://www.iftf.org/uploads/media/SR-1321_IFTF_FutureofPersuasionReport-1.pdf

Intille, S. S. (2004). A new research challenge: Persuasive technology to motivate healthy aging. *IEEE Transactions on Information Technology in Biomedicine*, *8*(3), 235–237. doi: 10.1109/TITB.2004.835531

Iovane, G., Salerno, S., Giordano, P., Ingenito, G., & Mangione, G. R. (2012, June). *A computational model for managing emotions and affections in emotional learning platforms and learning experience in emotional computing context*. Paper presented at the Sixth International Conference on Complex, Intelligent, and Software Intensive Systems (CICIS'12; pp. 873–880), Palermo, Italy. doi: 10.1109/CISIS.2012.207

Iyengar, M. S., Florez-Arango, J. F., & García C .A. (2009). GuideView: A system for developing structured, multimodal, multi-platform persuasive applications. *Proceedings of the Fourth Inernational Conference PERSUASIVE* (PERSUASIVE'09), Claremont, CA, USA. doi: 10.1145/1541948.1541990

Jaimes, A., & Sebe, N. (2007). Multimodal human–computer interaction: A survey. *Computer Vision and Image Understanding*, *108*, 116–134. doi: 10.1016/j.cviu.2006.10.019

Kaptein, M., Markopoulos, P., de Ruyter, B., Aarts, E., (2015) Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles, *International Journal of Human–Computer Studies*, *77*, 38–51. doi: 10.1016/j.ijhcs.2015.01.004

Karppinen, P., & Oinas-Kukkonen, H. (2013). Three approaches to ethical considerations in the design of behavior change support systems. In S. Berkovsky, & J. Freyne (Eds.), *Proceedings of the Eighth International Conference PERSUASIVE* (PERSUASIVE'13; pp. 87–98), Sydney, NSW, Australia. doi: 10.1007/978-3-642-37157-8_12

Kim, J., Ragnoni, A., & Biancat, J. (2010). In-vehicle monitoring of affective symptoms for diabetic drivers—in-vehicle hypoglycemia alerting system in EU project METABO. *Proceedings of the Third International Conference on Health Informatics* (HEALTHINF 2010; pp. 367–372), Valencia, Spain.

Kim, M., Kim, H. J., Lee, S. J., & Choi, Y. S. (2013). A touch based affective user interface for smartphone. *IEEE International Conference on Consumer Electronics* (ICCE; pp. 606–607). Las Vegas, NV, USA. doi: 10.1109/ICCE.2013.6487037

Kleinsmith, A., & Bianchi-Berthouze, N. (2013). Affective body expression perception and recognition: A survey. *IEEE Transactions on Affective Computing*, *4*(1), 15–33. doi: 10.1109/T-AFFC.2012.16

Kohl, L. F., Crutzen, R., & de Vries, N. K. (2013). Online prevention aimed at lifestyle behaviors: A systematic review of reviews. *Journal of Medical Internet Research, 15*(7), e146. doi: 10.2196/jmir.2665

Kraft, P., Schjelderup-Lund, H., & Brendryen, H. (2007). Digital therapy: The coming together of psychology and technology can create a new generation of programs for more sustainable behavioral change. *Persuasive Technology, Lecture Notes in Computer Science*, *4744*, 18–23. doi: 10.1007/978-3-540-77006-0_3

Kreuter, M. W., Farrell, D. W., Olevitch, L. R., & Brennan, L. K. (2000). *Tailoring health messages: Customizing communication with computer technology*. Mahwah, NJ, USA: Lawrence Erlbaum Associates, Inc., Publishers. ISBN-13: 978-0805833867

Leonard, L. N. K., & Haines, R. (2007). Computer-mediated group influence on ethical behavior. *Computers in Human Behavior, 23*, 2302–2320. doi: 10.1016/j.chb.2006.03.010

Li, C.-Y. (2013). Persuasive messages on information system acceptance: A theoretical extension of elaboration likelihood model and social influence theory. *Computers in Human Behavior*, *29*, 264–275. doi: 10.1016/j.chb.2012.09.003

Li, H., & Chatterjee, S. (2010). Designing effective persuasive systems utilizing the power of entanglement: Communication channel, strategy and affect. *Persuasive*, *6137*, 274–285. doi: 10.1007/978-3-642-13226-1_27

Lisetti, C., Nasoz, F., Lerouge, C., Ozyer, O., & Alvarez, K. (2003). Developing multimodal intelligent affective interfaces for tele-home health care. *International Journal of Human–Computer Studies*, *59*, 245–255. doi: 10.1016/S1071-5819(03)00051-X

Luneski, A., Bamidis, P., & Hitoglou-Antoniadou, M. (2008). Affective computing and medical informatics: State of the art in emotion aware medical applications. In S. K. Andersen, M. C. A. Klein, S. Schulz, J. Aarts, & M.C. Mazzoleni (Eds.), *eHealth beyond the horizon*; *Get IT there* (pp. 517–522). Amsterdam, the Netherlands: IOS Press. Retrieved August 22, 2013, from http://person.hst.aau.dk/ska/MIE2008/ParalleSessions/PapersForDownloads/05.HCI&IM/SHTI136-0517.pdf

Luneski, A., Konstantinidis, E., & Bamidis, P. D. (2010). Affective medicine: A review of affective computing efforts in medical informatics. *Methods on Information in Medicine*, *49*(3), 207–218. doi: 10.3414/ME0617

Maas, J, Hietbrink, L., Rincka, M., & Keijsers, G P. J. (2013). Changing automatic behavior through self-monitoring: Does overt change also imply implicit change? *Journal of Behavior Therapy and Experimental Psychiatry*, *44*(3), 279–284. doi: 10.1016/j.jbtep.2012.12.002

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, *35*(2), 293–334.

Madsen, M., el Kaliouby, R., Goodwin, M., & Picard, R. (2008). Technology for just-in-time in-situ learning of facial affect for persons diagnosed with an autism spectrum disorder. *Proceedings of the 10th International ACM SIGACCESS Conference on Computers and Accessibility* (Assets '08, pp. 19–26), Halifax, Nova Scotia, Canada. doi: 10.1145/1414471.1414477

Manton, K. (1989). Life-style risk factors. *Annals of the American Academy of Political and Social Science, 503*, 72–88. doi: 10.1177/0002716289503001006

Marcu, G., Bardram, J. E., & Gabrielli, S. (2011, May). *A framework for overcoming challenges in designing persuasive monitoring and feedback systems for mental illness*. Paper presented at the Fifth International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth; pp. 1–8), Dublin, Ireland. doi: 10.4108/icst.pervasivehealth.2011.246097

Marsch, L. A., Guarino, H., Acosta, M., Aponte-Melendez, Y., Cleland, C., Grabinski, M., Brady, R., & Edwards, J. (2014). Web-based behavioral treatment for substance use disorders as a partial replacement of standard methadone maintenance treatment. *Journal of Substance Abuse Treatment*, *46*(1), 43–51. doi: 10.1016/j.jsat.2013.08.012

Massachusetts Institute of Technology (MIT) Media Lab. (n.d.). Affective computing. Retrieved December 10, 2014, from http://affect.media.mit.edu/

Matsumoto, K., & Ren, F. (2011). Estimation of word emotions based on part of speech and positional information. *Computers in Human Behavior*, *27*, 1553–1564. doi: 10.1016/j.chb.2010.10.028

Merino Albaina, I., Visser T., van der Mast C., & Vastenburg M. (2009, April). *Flowie: A persuasive virtual coach to motivate elderly individuals to walk*. Paper presented at the Third IEEE International Conference on Pervasive Computing Technologies for Healthcare (pp. l–7), London, UK. doi: 10.4108/ICST.PERVASIVEHEALTH2009.5949

Mintz, J., & Aagaard, M. (2012). The application of persuasive technology to educational settings. *Educational Technology Research and Development*, *60*(3), 483–499. doi: 10.1007/s11423-012-9232-y

Mukhtar, H., Ali, A., Belaid, D., & Lee, S. (2012, June). *Persuasive healthcare self-management in intelligent environments*. Paper presented at the Eighth International Conference on Intelligent Environments (pp. 190–197), Guanajuato, Mexico. doi: 10.1109/IE.2012.51

Mumm, J., & Mutlu, V. (2011). Designing motivational agents: The role of praise, social comparison, and embodiment in computer feedback. *Computers in Human Behavior*, *27*, 1643–1650. doi: 10.1016/j.chb.2011.02.002

Munson, S. A. (2012, May). *Pervasive, persuasive health: Some challenges*. Paper presented at the Sixth International Conference on Pervasive Computing Technology for Healthcare (PervasiveHealth; pp. 241–244), San Diego, CA, USA. doi: 10.4108/icst.pervasivehealth.2012.248712

Nakajima, T., & Lehdonvirta, V. (2011). Designing motivation using persuasive ambient mirrors. *Personal and Ubiquitous Computing; 17*(1), 107–126. doi: 10.1007/s00779-011-0469-y

National Academy of Engineering of the National Academies [USA]. (2008). Grand challenges. Retrieved October 23, 2013, from http://www.engineeringchallenges.org/cms/challenges.aspx

Nguyen, H., & Masthoff, J. (2009). Designing empathic computers: The effect of multimodal empathic feedback using animated agent. *Proceedings of the Fourth International Conference on Persuasive Technology* (Persuasuve'09). doi: 10.1145/1541948.1541958

Nickel, P., & Spahn, A. (2012). Trust, discourse ethics, and persuasive technology. *Proceedings of the Seventh International Conference on Persuasive Technology* (Persuasive 2012; pp. 37–40), Linköping, Sweden: Linköping University Electronic Press.

Nummenmaa, L., Glerean, E., Hari, R., & Hietanen J. K. (2013). Bodily maps of emotions. In I. M. Verma, *Proceedings of the National Academy of Sciences of the USA* (PNAS) *111*(2), 646–51. doi: 10.1073/pnas.1321664111

Osgood, C. E., May, W. H., & Miron, M. S. (1975). *Cross-cultural universals of affective meaning*. Champaign, IL, USA: University of Illinois Press.

Osgood, C. E. & Treng, O. S. C. (Eds.) (1990). *Language, meaning, and culture: The selected papers of C. E. Osgood* (Centennial Psychology Series). New York, NY, USA: Praeger Publishers. ISBN-13: 978-0275925215.

Ottaviano, M., Vera-Muñoz, C., Arredondo, M. T., Salvi, D., Salvi, S., Páez, J. M., & Díaz de Barrionuevo, A. (2011, August). *Innovative self management system for guided cardiac rehabilitation*. Paper presented at the 33rd Annual International Conference of the IEEE EMBS, Boston, MA, USA. doi: 10.1109/IEMBS.2011.6090454

Ouweneel, E., Le Blanc, P. M., & Schaufeli, W. (2013). Do-it-yourself: An online positive psychology intervention to promote positive emotions, self-efficacy, and engagement at work. *Career Development International*, *18*(2), 173–195. doi: 10.1108/CDI-10-2012-0102

Pantic, M., Sebe, N., Cohn, J. F., & Huang, T. (2005). Affective multimodal human–computer interaction. *Proceedings of the 13th annual ACM International Conference on Multimedia* (MULTIMEDIA’05; pp. 669–676). doi: 10.1145/1101149.1101299

Pantic M., Valstar, M., Rademaker, R., & Maat, L. (2005). Web-based database for facial expression analysis. *Proceedings of the IEEE International Conference on Multimedia and Expo* (ICME; pp. 317–321), Amsterdam, the Netherlands. doi: 10.1109/ICME.2005.1521424

Pastor-Sanz, L., Vera-Munoz, C., Fico, G., & Arredondo, M. T. (2008). Clinical validation of a wearable system for emotional recognition based on biosignals. *Journal of Telemedicine and Telecare*, *14*(3), 52–54. doi: 10.1258/jtt.2008.003017

Patel, H., Bayliss, L. C., Ivory, J. D., Woodard, K., McCarthy, A., & MacDorman, K. F. (2014). Receptive to bad reception: Jerky motion can make persuasive messages more effective. *Computers in Human Behavior*, *32*, 32–39. doi: 10.1016/j.chb.2013.11.012

Pedersen, C. H., Khaled, R., & Yannakakis, G. N. (2012). Ethical considerations in designing adaptive persuasive games. *Proceedings of the Seventh International Conference on Persuasive Technology,* (pp. 13–16), Linköping, Sweden.

Peeples, M., Iyer, A. K., & Cohen, J. L. (2013). Integration of a mobile-integrated therapy with electronic health records: Lessons learned. *Journal of Diabetes Science and Technology, 7*(3), 602–611.

Personalized Monitoring Systems for Care in Mental Health Project (PSYCHE). (n.d.). Web site for the PSYCHE project of the European Union FP7 Information and Communication Technologies Research Area, ICT-2007 5.1 Personal Health Systems for Monitoring and Point-of-Care Diagnostics, Research Project No. FP7 247777. Retrieved December 9, 2014, from http://www.psyche-project.org/

Picard, R. W. (1995). *Affective computing.* M.I.T Media Laboratory Perceptual Computing Section Technical Report No. 321. Retrieved September 24, 2013, from https://www.pervasive.jku.at/Teaching/_2009SS/SeminarausPervasiveComputing/Begleitmaterial/Related%20Work%20(Readings)/1995_Affective%20computing_Picard.pdf

Picard, R. W. (1999). Affective computing for HCI. In H.-J., Bullinger, & J., Ziegler (Eds.), *Proceedings of the Eighth International Conference on Human–Computer Interaction: Ergonomics and User Interfaces*, (HCI International’99; pp. 829–833), Munich, Germany.

Picard, R. W. (2000). *Affective computing*. Boston, MA, USA: The MIT Press. ISBN: 9780262661157

Picard, R. W. (2002). Affective medicine: Technology with emotional intelligence. In R. Bushko (Ed.), *Chapter in future of health technology* (pp. 69–83). Amsterdam, the Netherlands: IOS Press. doi=10.1.1.94.1125

Picard, R. W. (2003). Affective computing: Challenges. *International Journal of Human–Computer Studies*, *59* (1–2), 55–64. doi: 10.1016/S1071-5819(03)00052-1

Ping, L. K., Poh, J. P., Meng L. K., Husain, W., & Adnan, M. H. M. (2012, June). *A framework of a childhood obesity intervention using persuasive web-mobile technology*. Paper presented at the International Conference on Computer & Information Science (ICCIS; pp. 50–54). Kuala Lumpur, Malaysia. doi: 10.1109/ICCISci.2012.6297211

Poria, S., Cambria, E., Hussain, A., & Huang, G.-B. (2015). Towards an intelligent framework for multimodal affective data analysis. *Neural Networks*, *63*, 104–116. doi: 10.1016/j.neunet.2014.10.005

Postolache, O., Girao, P. S., Ribeiro, M., Carvalho, H., Catarino, A., & Postolache, G. (2012, May). Treat Me Well: Affective and physiological feedback for wheelchair users. In V. Groza & A. M. L. Lanzolla, *Proceedings of the IEEE International Symposium on Medical Measurements and Applications,* (MeMeA, pp. 1–7), Budapest, Hungary. doi: 10.1109/MeMeA.2012.6226660

Pousman, Z., & Stasko, J. (2006). A taxonomy of ambient information systems: Four patterns of design. In *ACM Proceedings of the Working Conference on Advanced Visual Interfaces* (AVI’06, pp. 67–74), Venice, Italy. doi: 10.1145/1133265.1133277

Quinn, C. C., Shardell, M. D., Terrin, M. L., Barr, E. A., Ballew, S. H., & Gruber-Baldini, A. L. (2011). Cluster-randomized trial of a mobile phone personalized behavioral intervention for blood glucose control. *Diabetes Care*, *34*(9), 1934–1942. doi: 10.2337/dc11-0366

Reisenzein, R., Hudlicka, E., Dastani, M., Gratch. J., Hindriks, K., Lorini, E., & Meyer, J.-J. C. (2013). Computational modeling of emotion: Toward improving the inter- and intradisciplinary exchange. *IEEE Transactions on Affective Computing*, *4*(3), 246–266. doi: 10.1109/T-AFFC.2013.14

Reitberger, W., Meschtscherjakov, A., Mirlancher, T., Scherndl, T., Huber, H., & Tscheligi, M. (2009). A persuasive interactive mannequin for shop windows. *Proceedings of the Fourth International Conference on Persuasive Technology* (Persuasive'09), Claremont, California, USA. doi: 10.1145/1541948.1541954

Reiter, H., Tesanovic, A., & Martinez-Romero, A. (2013, July). *HeartCycle: From insights to clinically evaluated ICT solutions for telehealth*. Paper presented at the 35th Annual International Conference of the IEEE EMBS, (EMBC'13; pp. 6992–5), Osaka, Japan. doi: 10.1109/EMBC.2013.6611167

Rodríguez, M. D., Roa, J. R., Morán, A. L., & Nava-Muñoz, S. (2012, May). *Persuasive strategies for motivating elders to exercise*. Paper presented at the Sixth International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth, pp. 219–223), Baja California, Mexicali, Mexico. doi: 10.4108/icst.pervasivehealth.2012.248774

Royal Academy of Engineering. (2013). *Global grand challenges summit, 2013*. Retrieved October 13, 2013, from http://www.raeng.org.uk/international/global_grand_challenges_summit.htm

Ruggiero, D. (2015). The effect of a persuasive social impact game on affective learning and attitude. *Computers in Human Behavior*, *45*, 213–221. doi: 10.1016/j.chb.2014.11.062

Rutkowski, T. M., Tanaka, T., Cichocki, A., Erickson, D, Jianting Cao, J., & Mandic, D. P. (2011). Interactive component extraction from fEEG, fNIRS and peripheral biosignals for affective brain–machine interfacing paradigms. *Computers in Human Behavior*, *27*, 1512–1518. doi: 10.1016/j.chb.2010.10.016

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston, MA, USA: Houghton, Mifflin and Co.

Sharp, P. A. (2012, October). *Convergence as the third revolution*. Paper presented at the IEEE Life Sciences Grand Challenges Conference, (LSGCC), Washington DC, USA. Retrieved on September 15, 2013 from: http://lifesciences.ieee.org/images/pdf/2012lsgc-sharp.pdf

Shih, F. Y., & Chuang, C.-F. (2008). Performance comparisons of facial expression recognition in JAFFE database. *International Journal of Pattern Recognition & Artificial Intelligence*, *22*(3), 445–459.

Steephen, J. (2013). HED: A computational model of affective adaptation and emotion dynamics. *IEEE Transactions on Affective Computing*, *4*(2), 197–210. doi: 10.1109/T-AFFC.2013.2

Tan, C. S. S., Schöning, J., Luyten, K., & Coninx, K. (2013). Informing intelligent user interfaces by inferring affective states from body postures in ubiquitous computing environments. *Proceedings of the International Conference on Intelligent User Interfaces* (IUI'13; pp. 235–246), Santa Monica, CA, USA. doi: 10.1145/2449396.2449427

Thompson, E. R. (2007). Development and validation of an internationally reliable short-form of the positive and negative affect schedule (PANAS). *Journal of Cross-Cultural Psychology*, *38*(2), 227–242. doi: 10.1177/0022022106297301

Torning, K., & Oinas-Kukkonen, H. (2009). Persuasive system design: State of the art and future directions. *Proceedings of the Fourth International Conference on Persuasive Technology* (Persuasive'09; Article No. 30), Claremont, CA, USA. doi: 10.1145/1541948.1541989

Valenza, G., Gentili, C., Lanatà, A., & Scilingo, E. (2013). Mood recognition in bipolar patients through the PSYCHE platform: Preliminary evaluations and perspectives. *Artificial Intelligence in Medicine*, *57*, 49–58. doi: 10.1016/j.artmed.2012.12.001

Valstar, M., Schuller, B., Smith, K., Eyben, F., Jiang, B., Bilakhia, S., Schnieder, S., Cowie, R., & Pantic, M. (2013, October). *AVEC 2013: The continuous audio/visual emotion and depression recognition challenge*. Paper presented at the ACM-Multimedia Conference, Barcelona, Spain. Retrieved November 30, 2013, from http://www.cs.nott.ac.uk/~mfv/Documents/avec2013.pdf van den Broek, E. L. (2013). Ubiquitous emotion-aware computing. *Personal and Ubiquitous Computing*, *17*(1), 53–67. doi: 10.1007/s00779-011-0479-9

Verhagen, T., Feldberg, F., van den Hooff, B., Meents, S., & Merikivi, J. (2012). Understanding users' motivations to engage in virtual worlds: A multipurpose model and empirical testing. *Computers in Human Behavior*, *28*, 484–495. doi: 10.1016/j.chb.2011.10.020

Wang, S., Liu, Z., Wang, Z., Wu, G., Shen, P., He, S., & Wang, X. (2013). Analyses of a multimodal spontaneous facial expression database. *IEEE Transactions on Affective Computing*, *4*(1), 34–46. doi: 10.1109/T-AFFC.2012.32

Wang, W. Y., Ko, L. C., Huang, Y. M., Liu, Y. R., & Lin, S. M. (2014). What is affective learning? Advanced technologies, embedded and multimedia for human-centric computing. *Lecture Notes in Electrical Engineering*, *260*, 177–181. doi: 10.1007/978-94-007-7262-5_20

Watson, D., Clark, L. A., & Tellegen, D. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*, 1063–1070.

Wilson, E. V., & Lu, Y. (2008). Communication goals and online persuasion: An empirical examination. *Computers in Human Behavior*, *24*, 2554–2577. doi: 10.1016/j.chb.2008.02.021

Wu, D. (2012, June). *Fuzzy sets and systems in building closed-loop affective computing systems for human–computer interaction: Advances and new research directions*. Paper presented at the IEEE International Conference on Fuzzy Systems, (FUZZ-IEEE; pp. 1–8), Brisbane, Australia. doi: 10.1109/FUZZ-IEEE.2012.6250779

Yang, P.-C., Chiang, J.-H., Liu, J.-C., Wen, Y.-L., & Chuang, K.-Y. (2010, December). *An efficient cloud for wellness self-management devices and services*. Paper presented at the Fourth International Conference on Genetic & Evolutionary Computing, (ICGEC, pp. 767–770), Shenzhen, China. doi: 10.1109/ICGEC.2010.194

Yeh, J.-H., Pao,T.-L., Lin, C.-Y., Tsai, Y.-W, & Chen, Y.-T. (2011). Segment-based emotion recognition from continuous Mandarin Chinese speech. *Computers in Human Behavior*, *27*, 1545–1552. doi: 10.1016/j.chb.2010.10.027

Zhang, C., & Wang, J. (2013). Affective computing model for the set pair users on Twitter. *International Journal of Computer Science Issues*, *10*(1), 347–353.

Authors' Note

This research was conducted without specific funding from any public or private agency.

All correspondence should be addressed to
Rebeca I. García-Betances
Life Supporting Technologies (LifeSTech)
Escuela Técnica Superior de Ingenieros de Telecomunicación (ETSIT)
Universidad Politécnica de Madrid (UPM), Campus Moncloa
Avenida Complutense nº 30, Ciudad Universitaria, Madrid 28040, Spain
rgarcia@lst.tfo.upm.es

Human Technology: An Interdisciplinary Journal on Humans in ICT Environments
ISSN 1795-6889
www.humantechnology.jyu.fi