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Toward a Taxonomy of Affective Computing

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Affective computing, which is the topic concerned with the design of emotionally intelligent machines, has been a growing area of interest in the field of human–computer interaction. Many of the current questions in the field will need to be answered in order for progress to be made toward a truly affective computing platform. The current article seeks to summarize much of the existing research in affective computing focused in three primary areas: affective generation, affective understanding, and application. A taxonomy of affective computing applications is then proposed in an effort to help organize the efforts of researchers and designers alike. This taxonomy contains a hierarchy of five tiers: the purpose or goal of the system, the level of integration, the method of affective understanding, the method of affective generation, and the platform of use. The article concludes by highlighting several key issues that the field of affective computing faces moving forward.

1. INTRODUCTION

Affective computing is the field of designing machines that can recognize, express, communicate, and respond to humans using emotions. The goal of affective computing is to use the positive, affective communication found in human–human interaction and apply it to human–computer interaction. The principles of affective computing rest within the field of human factors on the topic of human–computer interaction (Karwowski, 2005) and the finding that humans interact socially with computers and machines, similar to the way humans interact with other humans (McEneaney, 2013; Muir, 1988; Reeves & Nass, 1996). Based on this notion, it is likely that human–computer interaction can be enhanced using the same principles that govern human–human interaction etiquette (Miller, 2002) and practitioners that take affect into account could see higher productivity and performance (Norman, Ortony, & Russell, 2003). Although it is likely beyond the realm of possibility for a computer to truly feel emotion in the sense that humans do, affective computers need only express emotions, not feel them (Picard, 2003). This leads to a clear and important distinction in affective computing between feeling and expressing emotions.

The organization of affective computing research is not widely agreed upon. For example, Carberry and de Rosis (2008) defined four areas of development: analysis of affective states, automatic recognition of affective states, adapting system response to affective states, and designing avatars to exhibit appropriate affective states. For the purpose of this article, I use the three slightly broader areas defined by Tao and Tan (2005): affective understanding, affective generation, and application. Affective understanding is the ability for a computer to understand the affective state of its user. Affective generation is the ability for a computer to make an emotional response that at least appears genuine and has a positive impact on the user. Application involves research into which areas affective computing could be utilized and which facets of the task could be improved with affective computing.

The objective of this article is threefold. First, the article seeks to broadly cover general principles of affect, both in understanding and generation, found in the psychology literature. Much of the groundwork for affective computing platforms has been laid by psychologists (even if unknowingly), and this article seeks to provide a summary of that work and those topics. Second, the article discusses application and provides a summary of some of the work done within the field of affective computing in regards to the topics of affective understanding and affective generation. Finally, the article lays a foundation for future work in affective computing by proposing a taxonomy for guiding work on future affective computing applications, and it concludes by highlighting several important questions for affective computing researchers.

2. AFFECTIVE UNDERSTANDING

For affective computing to be implemented successfully in practical applications, computers need to interpret the affective state of their users. Without this information, a computer would not be able to make an appropriate response. Because affective understanding represents a clear starting point, most of the research in affective computing has been focused in this domain (Carberry & de Rosis, 2008). Research in

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affective understanding is generated by psychological research in affective understanding in humans. This research takes the cues that allow humans to understand the affective state of other humans as a starting point for affective understanding in computers. Some examples of these cues are emotional speech, facial expression, gestures, and physiological measures such as heart rate and skin conductivity. Although each of these examples has shown moderate success in affective computing, each contain significant limitations as well (some of which are outlined in this article). True affective understanding will likely be achieved only through a combination of methods in order to circumvent each method's shortcomings.

2.1. Modalities

Emotional speech perception. Emotional speech processing in affective computing is an area that has borrowed heavily from research findings in psychology. For example, one of the established psychological principles of emotional speech perception is that the acoustic features of speech (e.g., pitch, loudness, and intonation) vary based on the speaker's affect (Jaywant & Pell, 2012; Rodero, 2011; Scherer, 1986). Other aspects of the voice that change with affect are speaking rate (Petrushin, 2000) and voice quality (e.g., raspiness; Gobl & Chasaide, 2003). Banse and Scherer (1996) presented judges with professional actors' portrayals of 14 different emotions that varied in intensity and valence. Accuracy for human judges was relatively high for "hot anger" (78%), "boredom" (76%), and "interest" (75%); lower for "fear" (63%) and "anger" (51%); and quite low for "shame" (22%) and "disgust" (15%). Still, their results show that, despite variability, human judges were able to recognize virtually all types of emotion with "much-better-than-chance" accuracy. Of perhaps greater importance to affective computing, an acoustical analysis of the portrayals supported most of Scherer's (1986) original hypotheses regarding emotion and acoustic features, such as fundamental frequency, mean energy, energy distribution, and speech rate. This research demonstrates that the acoustic features of speech do generally change in a predictable fashion with the affect being portrayed by the speaker. There have already been efforts made to adapt these findings of emotional speech perception from psychology to the domain of computers (Campbell, 2004; Massaro, Beskow, Cohen, Fry, & Rodriguez, 1999; Matsumoto & Ren, 2011).

Petrushin (2000), for example, created an emotion recognition agent that was able to analyze telephone speech signals and distinguish between "agitation" and "calm" with 77% accuracy. However, despite work such as this and the finding that changes in speech are strongly correlated with changes in affect, significant hurdles still remain for using speech to detect affect. For starters, the variations between different affective states are not always distinguishable. Scherer (1986) noted that researchers have found that both anger and happiness illicit a higher pitch, larger variability, faster tempo, and louder volume than in normal speech, which makes automated attempts to distinguish between the two more difficult. In addition, to use speech processing as a means for affective understanding, the program or platform would need to use speech as a primary user input. Computers typically use a mouse and keyboard for input, not speech. Using speech input would require a significant redesign of computing systems and software. However, some research has begun to examine how typical computer inputs can be used to estimate affect, including typing speed (Vizer, Zhou, & Sears, 2009) and squeeze pressure on a computer mouse (Van Galen, Liesker, & De Haan, 2004).

Facial expressions. Facial expressions are one of the paramount ways that humans display and recognize emotions and one of the most widely researched topics, regarding emotion, in psychology (Ekman & Friesen, 1978). The connection between facial expressions and emotion can be traced back to work by Darwin (1872), and ample psychological research since then has shown a strong connection between emotion and facial expressions (Ekman & Friesen, 1978; Etcoff & Magee, 1992; Izard, 1994; Jack, Caldara, & Schyns, 2012; Matsumoto & Willingham, 2009). As de Gelder, Teunisse, and Benson (1997) pointed out, however, our perception of emotional facial expressions may be due to our experience of facial expressions built up over the course of communicative development rather than a biological ability for humans to recognize facial expressions. The former would present a challenge to establishing a universal categorization for facial expressions, which one might hope to use for affective systems, due to different individual experiences. However, research has found substantial evidence for a biological, categorical basis for expression recognition, which has led to attempts to categorize facial expressions (de Gelder et al., 1997; Etcoff & Magee, 1992). In fact, facial expressions are such a strong indicator of emotion that some researchers considered it a hard-wired human behavior, making it a "universal language" of sorts (Izard, 1994; Matsumoto & Willingham, 2009). Ekman (1993), for example, found universality in both spontaneous and deliberate facial expression. The emotional effects of facial processing can even be observed in event-related potentials in the brain (Vuilleumier, Armony, Driver, & Dolan, 2001).

Perhaps of most importance to the field of affective computing was that the finding that facial expressions were emotion specific prompted the search for emotion-specific physiological changes (Ekman, 1999). Researchers in affective computing have picked up on the research of facial expressions from psychology in an attempt to apply the findings to computers. The goal, of course, is to design a computer that can use images of the user's current facial expression to estimate the current affective state of the user. To this end, work has been done in an attempt to translate facial expressions into something that computers can understand (Calder, 2001; Lyons, Akamatsu, Kamachi, & Gyoba, 1998).

However, like speech perception, the link between facial expressions and emotion is not perfectly clear. For example, despite the finding that many facial expressions are universal and found across cultures, many cultural and individual differences have also been found (Besel & Yuille, 2010; Elfenbein, Beaupre, Levesque, & Hess, 2007; Jack et al., 2012; Marsh, Elfenbein, & Ambady, 2003; Nisbett & Masuda, 2003; Russell, 1994). For example, Elfenbein and colleagues (2007) found differential muscle activation between participants from Quebec and Gabon for serenity, shame, contempt, anger, sadness, surprise, and happiness, whereas fear, disgust, and embarrassment were relatively similar. In addition, the meaning of emotional expressions can be confused. For example, babies suffering from colic will often "smile" in their sleep, but this is likely a grimace brought about by pain rather than pleasure (Labarre, 1947). The body of literature detailing cultural and individual differences in emotional facial processing has largely been ignored in the affective computing domain and presents another significant hurdle moving forward.

Gestures and body movement. Gestures and body movement are another way that humans display emotions and detect emotions in others (Atkinson, Tunstall, & Dittrich, 2007; de Gelder, 2006). Psychological studies have found that emotion can be recognized in body posture (Atkinson, Dittrich, Gemmell, & Young, 2004; Coulson, 2004), arm movement (Pollick, Paterson, Bruderlin, & Sanford, 2001), and whole-body movement (Atkinson et al., 2004). Not only are gestures associated with certain emotions, approval and insult gestures elicit different patterns of brain activity in the person viewing the gesture (Flaisch, Häcker, Renner, & Shupp, 2011). Emotional gestures and body movement have been translated to affective computing through apparentness methods and 3-D modeling (Aggarwal & Cai, 1999; Gavrila, 1999).

Similar to facial expression, the emotional meaning of gestures can vary on an individual and cultural basis (Archer, 1997; Labarre, 1947; Morris, 1994; So, 2010). Labarre (1947) noted several cultures that have gestures to signal disapproval and approval that are contrary to our own shaking and nodding of the head, such as hand waving (Ainu), eye movements (Semang), eyebrow movements (Abyssinians), and shoulder movements (Bengali). These differences can represent a problem for affective computing systems and add a significant amount of variability and diversity to the number of gestures and body movements that need to be detected and interpreted.

Physiological measures. As eluded to earlier with regard to facial expressions, studies in psychology have shown that emotions can elicit different physiological changes that can be measured directly, such as breathing, perspiration, blood pressure, heart rate, and muscle contractions (Coutinho & Cangelosi, 2011; Mella, Conty, & Pouthas, 2011; Stemmler, 2003). For example, changes in emotion from listening to music can be detected through changes in skin conductance and heart rate (Coutinho & Cangelosi, 2011). Physiological measures are typically correlated with intense emotions that cause arousal (Stemmler, 2003). These measures have been used in an attempt to predict affect (or stress) in affective computing scenarios (Healey, Picard, & Dabek, 1998; Ward & Marsden, 2003) and have been used in pattern classification analysis, a physiological method of detecting emotions (Kolodyazhniy, Kreibig, Gross, Roth, & Wilhelm, 2011). Kolodyazhniy and colleagues (2011) found that pattern classification analysis is fairly accurate (77.5%) at measuring and predicting certain affective states.

Although physiological measures can be used with some success at estimating affect, it is important to note that the relationship is correlational and not causal. Emotions have been shown to elicit physiological responses, but physiological responses can also elicit emotions (Blanchette & Leese, 2011). They are also quite dependent on individual differences. Of interest, just the thought of interacting with a humanlike robot is enough to increase blood pressure and negative affect in some individuals (Broadbent & Lee, 2011). Another problem is that physiological measures require monitoring, and current monitoring techniques are quite invasive. Users may find that the benefits from affective computing might not outweigh the costs of being hooked up to a wall of equipment while using the system. Efforts have been made to use the mouse and keyboard to take physiological measurements (Van Galen et al., 2004; Vizer et al., 2009), and it certainly seems plausible that measurements such as skin conductivity and heart rate could be detected through a mouse and keyboard as well. Still, significant technological advancement is needed in order to make the measurement of physiological measures natural and noninvasive.

2.2. The Synthesis Problem

An important note to be made regarding emotional recognition and the modes previously discussed in this section is that they represent an analysis of emotion. That is, using vocal, facial, gestural, and physiological cues to interpret emotion requires an analysis of the user's current affective state. However, some models of emotional recognition within artificial intelligence do not necessarily involve the recognition of emotion but attempt to simulate the mechanisms responsible for the production of emotion (Pfeifer, 1988). In other words, if a computer knows what makes someone happy, sad, fearful, and so on, and identifies only "happy" factors present, it could confidently predict happiness without being able to detect happiness in a user's voice, face, or body language.

Picard (2000) referred to these as "synthesis" models, and their use in affective computing is somewhat limited. The synthesis problem is illustrated by Picard's example of a computer that knows someone won the lottery and thus expects elation from them but cannot account for their look of distraught due to being unable to find their winning lottery ticket. However, it is also important to point out that perfect analysis methods can also be fooled, such as in Labarre's (1947) example of the smiling baby with colic. Although even humans are not always flawless in interpreting the emotions of others, we are generally able to easily and effortlessly combine synthesis and analysis for full emotional recognition. This highlights how important it is for affective computers to be able to analyze the emotional expression of a user.

3. AFFECTIVE GENERATION

Once computers are able to reliably measure and asses a user's current affective state, the next step is generating an affective change in the user. The purpose of affective computing can change drastically depending on the context, but the one similarity is the goal of using affect to improve or enhance some aspect of the user's interaction. To this end, the same psychological principles and theories used in affective understanding can be used in affective generation, similar to the relationship between learning to read words and learning to write words. Just as speech, facial expressions, and body language are used to assess affect, these mechanisms can also be used to generate affect that can be interpreted by the user.

Similar to affective understanding, the most successful affective generation will likely involve a combination of techniques. This is similar to human–human interaction, where it is far easier to appropriately estimate the emotion of an individual when using both facial and vocal cues, for example (Besel & Yuille, 2010). Affective generation also depends a great deal on the platform of the system. Traditional personal computers do not possess faces, limbs, or bodies to generate facial expressions, gestures, or postures. However, artificial avatars (e.g., the Microsoft paper clip) can be created with all of these attributes. An avatar is the embodiment of the computer, giving the computer a distinct character and features not typically associated with computers (Schroeder, 2002). Robots are another platform that can be used to express emotional gestures and body movements (Li & Chignell, 2011).

The nature of the task is one of the largest determinants of how sophisticated affective generation (and possibly affective understanding) needs to be. For example, if an automated, affective computing system were installed in the "lost luggage" department of an airline company, it is fairly safe to assume that the affect of each user it interacts with is going to be negative (happiness would be an atypical emotion to feel after the airline lost your luggage). In this case, an affective computing system would only need to be able to generate affect that would appease the user (e.g., positive, remorseful, sympathetic, etc). However, an affective system that was designed to tutor students in math would need to detect and generate a much larger range of affective states. Appeasement would not be sufficient to properly encourage and motivate all students.

4. CURRENT AFFECTIVE COMPUTING PROJECTS

Although the measurement and assessment of affect remains an imprecise science, efforts have still been made toward the development of affective computing systems. Tao and Tan (2005) listed several of these projects that are currently under development, and many more have been developed since their list was published. HUMAINE (Human–Machine Interaction Network on Emotion; http://emotion-research.net/) is a project designed to register, model, and influence human affect (Cowie, 2005). The Affective-Cognitive Framework for Learning and Decision-Making was an effort by MIT (http://affect.media.mit.edu/) to develop new models that integrate machine-learning, decision-making, cognitive, and affective models. New efforts, such as FaceSense, focus on evaluation tools for emotional expression from facial-head movements. The Birmingham Cognition and Affect Project (http://www.cs.bham.ac.uk/research/projects/cogaff/) is an effort to design architectures that can account for moods, emotions, desires, and other mental states and processes. The University of Sydney's Positive Computing Lab (http://www.positivecomputing.org/p/about.html) is conducting work on affect-aware intelligent tutoring systems. The University of Cambridge (http://www.cl.cam.ac.uk/research/rainbow/emotions/) is working on emotionally intelligent interfaces, with emphasis in affective robots for autism, body movement analysis, and facial tracking and affect inference, among others. The Vibe group at Microsoft (http://research.microsoft.com/en-us/um/redmond/groups/vibe/vibewebpage/) has several programs in development, such as AffectAura, which uses audio, visual, physiological, and contextual data to predict user affective states.

Other projects that are related to affective computing involve research in human–robot interactions. The Project on People and Robots from Carnegie Mellon University (http://www.peopleandrobots.org/) focuses on several aspects of human–robot interaction, including the design of appropriate appearance and interactions of robots in service contexts. IBM has been working on BlueEyes (http://www.almaden.ibm.com/cs/BlueEyes/), a project that aims to create computer systems with perceptual abilities akin to a human. IBM also recently created Watson, a robot that uses voice input to quickly aggregate information in order to answer questions with alarming speed and accuracy, even beating champions on the Jeopardy! game show. Vanderbilt University (http://eecs.vanderbilt.edu/cis/irl/) has projects dedicated to the development of affect-sensitive robotics, using physiological monitors such as heart rate, brainwaves, skin conductance, blood pressure, and temperature.

As can be seen from just this small sampling, the number of topics of investigation in affective computing is quite large and, although many of these projects have resulted in significant progress being made within their respective areas, it is difficult to identify a unified headway for the progression of the field as a whole. Each project has very different goals, very different levels of integration, and there is substantial variety in the methods and modalities that projects are using for affective understanding, generation, or both. It is hoped that the creation of an affective computing taxonomy will help provide a place to start unifying many of these existing projects so that those sharing similarities with one another can assist in building a more cohesive understanding of affective computing.

5. AFFECTIVE COMPUTING TAXONOMY

Many researchers list examples of affective computing applications, several of which already have made strides toward implementation, as just discussed. One problem with trying to create a concrete categorization of applications is that the potential influence of affective computing is unknown. Much of this influence will be moderated by the success and complexity of affective computing systems. If the systems are small and inflexible with very narrow scopes, affective computing will likely be designed for a limited number of domains and only for extremely specific purposes. If technology allows affective computing systems to become large and adaptive, it is possible that these systems would influence nearly every aspect of life. The potential for affective computing is large and likely limited only by technology and our ability to implement the systems.

Due to the immense variety of possible affective computing applications, the affective computing taxonomy presented in this article (see Figure 1) uses a similar design to Bloom's (1956) Taxonomy instead of relying on predetermined, artificial, and constrained categories. At each level of the taxonomy, starting with the bottom, a categorical decision is made regarding the design of the affective computing system. The number of possible categories is undefined in order to incorporate the boundless number of potential designs and applications of affective computing (e.g., Figure 2).

The taxonomy itself contains five levels. These are levels where decisions must take place for all affective computing systems that would be implemented in society. At the first level, the lowest level, the purpose or the goal of the system must be defined. Some examples of purpose could be education, service, or entertainment. Determining purpose is an essential first step in the design of a system because all other decisions about the system must take into account the goal of the system. The second level is integration. One must decide how integrated into society the system should be. For example, if the goal or purpose of the system is education, is the system going to replace or simply assist human educators? If it is going to assist human educators, will it take over any tasks from them, or will it only assist on some tasks? How many tasks? These are all questions that must be answered at the integration level and will further determine the characteristics of the system.

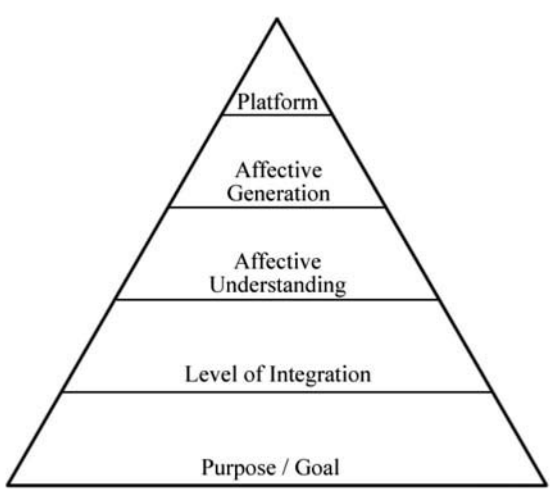

FIG. 1. Taxonomy for affective computing design.

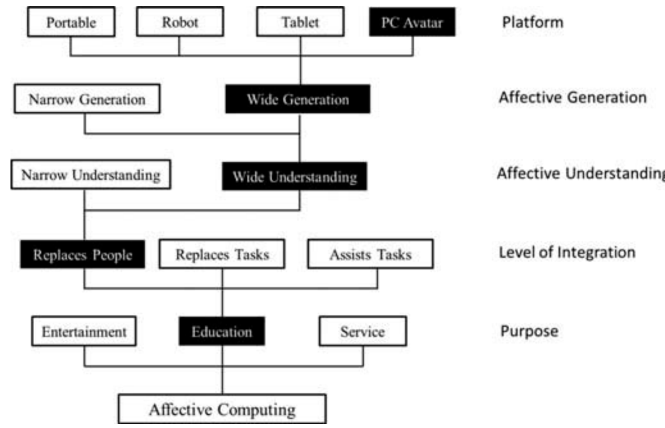

FIG. 2. A sample of the affective computing taxonomy in use. *Note.* In this case, the selected affective computing application is an educational tutor that is designed to replace people, possess a wide understanding and ability to generate affect, and is best represented as a PC avatar platform due to the affective needs of this system. Selected items in the taxonomy are represented in black.

The next two levels, affective understanding and generation, are the affective levels, which address the degree to which the system needs to understand and express affect. The answers to these questions will depend on the decisions made at the first two levels. For example, an affective computing system intended for customer support would have vastly different affective requirements than a system intended for education, and a system intended to replace a human educator would have different demands than a system designed to assist a human educator. Furthermore, it is likely that a system will need to understand more affect than it needs to generate. Returning to our example of the lost baggage system, it would need to understand anger and frustration as well as happiness and appeasement, so it would be able to monitor its effectiveness. However, it would be counterproductive for the system to actually generate anger and frustration, even though it needs to be able to detect them. In a system such as an educational tutor, the difference between the amount of affective understanding and affective generation needed may be much smaller because optimal motivational and teaching styles differ drastically among individuals, demanding a larger variety of affective generation.

Finally, the platform of the system needs to be determined. This will depend on the choices made at the previous four levels. For example, a service system designed to assist the elderly would likely need physical functionality, in which case a robotic structure may be required. A system that does not need immense affective generation may be adequate as a standard PC program that speaks to the user, whereas a program that requires a large amount of affective generation would likely need facial and body movements, necessitating an avatar. Just as the computing world has taken on new platforms, it is likely that the affective computing platforms will be diverse and new technologies will lead to platforms that are difficult to account for today.

6. ISSUES FOR AFFECTIVE COMPUTING

A theme taken from each of the affective understanding areas is that individual differences play an extremely large role in emotion, whether personal differences or cultural differences. Existing models in affective computing tend to use highly stereotyped personality types and emotional responses, which do not relate well to actual behavior (Tao & Tan, 2005). With the number of variables that need to be accounted for in affective computing, the task seems almost insurmountable. However, proper modeling can and *should* resolve these problems (Picard, 2003). Developing an affective computing design that cannot function and interact with real human behavior is hardly a desirable goal, so these individual differences must be taken into account (McNeese, 2003; Szalma, 2009).

The task, then, for affective computing researchers is to begin taking the individual difference findings in emotion from psychology and start applying them to human–computer interaction. A concrete understanding and representation of individual differences will go far in successfully moving affective computing designs and models from the drawing board to the real world. Neglecting individual differences will result in a failure of the systems to be adaptable enough to make a robust impact on the user.

This is not the first time that criticisms of this nature have been raised. Picard (2003) noted two similar criticisms of affective computing. The first is that "the range of means and modalities of emotion expression is so broad, with many of these modalities being inaccessible (e.g., blood chemistry, brain activity, neurotransmitters), and many others being too non-differentiated" (p. 56). The second is that "people's expression of emotion is so idiosyncratic and variable, that there is little hope of accurately recognizing an individual's emotional state from the available data" (p. 56). Each of these criticisms ultimately breaks down to the large variation in the expression of emotion and the monumental task of measuring these emotions, variations that hinge on individual differences.

To address these criticisms, Picard (2003) drew some similarity between affect recognition and speech recognition. Specifically, speech recognition must take into account many individual variances in voice. Even so, major advances have been made in speech recognition to the point where programs can quite reliably recognize and translate speech. Picard also noted the importance of partial understanding, specifically citing an infant's ability to understand some expressions long before they understand language. Even if we cannot perfectly measure all modalities of affect, predicting some is a good start and a base off which to build.

Another issue that affective computing must tackle is the way in which people react to the display of emotions. Recent research has found that highly neurotic women and highly narcissistic men are more susceptible to affect change as a result of affective feedback from a computer (Schwark, Dolgov, Hor, & Graves, 2013). A large body of psychological literature examines the different ways that individuals respond to emotional stimuli (Charles, Reynolds, & Gatz, 2001; Costa, McCrae, & Arenberg, 1980; Matthews, Deary, & Whiteman, 2003; Mroczek & Kolarz, 1998). Although some of these findings have made it into the computing literature (Chou & Chen, 2009; Johnson, Veltri, & Hornik, 2008; Lavie & Meyer, 2010; Szalma, 2008, 2009), most models of affective computing rarely take into account the end result of the effect on the user, instead focusing more on affective understanding and generation (Picard, 2003). The end result of the effect on the user needs to be taken into account so that it is possible to assess the impact of an affective system; otherwise the system may not be performing its intended function even if it is successful in understanding and generating affect.

7. CONCLUSION

This article provides a general overview of affective computing, starting with its basis in past psychological research and continuing to current affective computing projects being developed today. Also covered is what is generally understood to date about a human and a computer's ability to understand and generate affect. The affective computing taxonomy was created with the purpose of focusing research in affective computing by allowing researchers to more easily identify commonalities between efforts. Using a simple and flexible method to classify systems should help move efforts toward a more unified theory of affective computing. Finally, the future issues for affective computing brings to light several areas that have thus far been relatively neglected in the field but are areas that should be addressed before truly flexible affective computing is attainable.

Affective computing remains in its infancy, and many of the issues raised here may seem minor distractions from the work that is being conducted currently. However, these are all issues that must be taken into account in order for affective computing to work properly. Individual differences and the impact on the user should be taken into consideration in affective computing models and designs from the beginning of development so that they can be fully integrated into systems. Successful development of an affective computing system could revolutionize the computer industry and our way of life like few things have, which should continue to motivate affective computing research moving forward.

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